GRASPING

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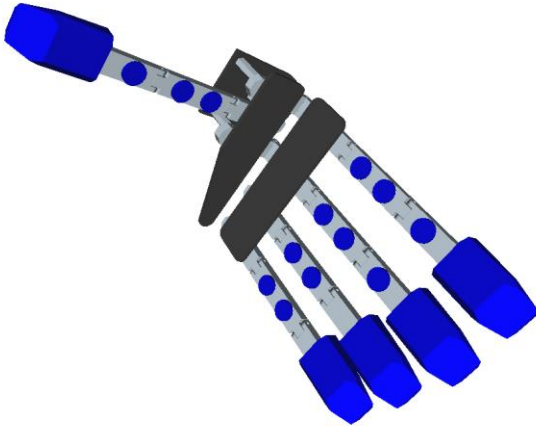
High Performance Humanoid Technologies (H2T)



Outline

- Building humanoid robots
  - Biomechanical models of the human body
  - Mechatronics of humanoid robots
- Grasping
  - Grasping in humans
  - Grasping Taxonomies
  - Grasping familiar and unknown objects
- Active Perception
  - Active vision and active touch
  - Visuo-haptic exploration
- Imitation-learning & Programming by Demonstration: Observation, representation and reproduction
  - Acquisition and analysis of human motion
  - Action representations: DMPs, HMMs, Splines
  - Mapping and motion reproduction
- From Signals to Symbols
  - From features to objects and from motions to actions
  - Object-Action Complexes: Semantic sensorimotor categories
  - AI & Robotics

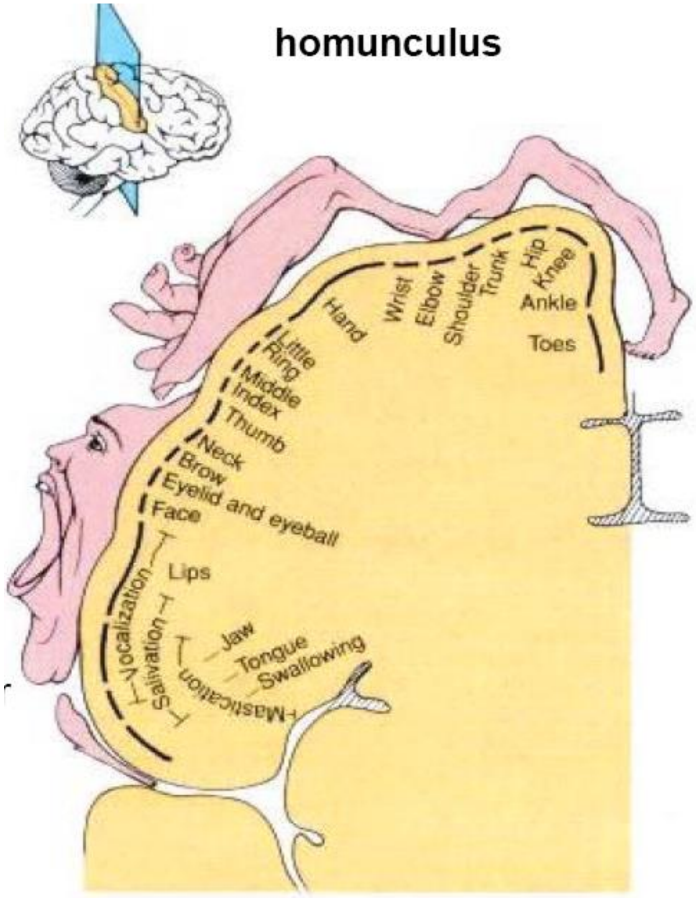
Grasping

- Fundamentals and definitions
- Grasping in humans "Neuroscience of grasping"
- Human Hand models
- Grasping Taxonomies
- Postural Synergies and Eigengrasps
- Implementation of synergies in robotics
- The TUAT/Karlsruhe Humanoid Underactuated Hand
- Eigengrasps: Grasp planning based on postural synergies
- Grasping known, familiar and unknown objects

Cognitive Grasping

- Grasping and manipulation as a control problem have been studied since the beginning of robotics: HOWEVER - very little has been done in terms of cognitive aspects of grasping, implementation and evaluation of systems

- Large part of the human cortex is dedicated to grasping and manipulation, and it would seem reasonable to assume that all of this cognitive machinery is dedicated to finely controlling individual joints and generating highly flexible hand postures

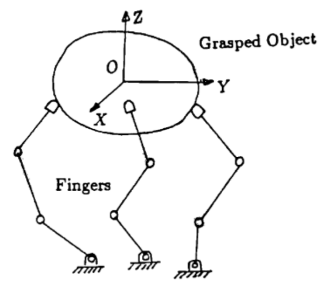


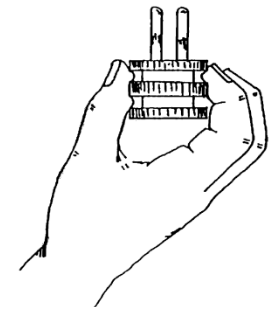
- Understanding how the human brain controls the hand

Understanding hands = Understanding Intelligence

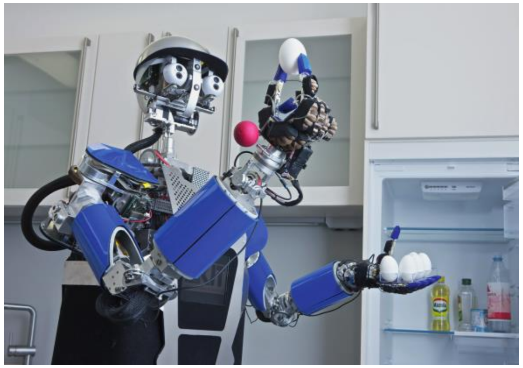
What is a grasp?

- A system wherein a desired object is gripped by the fingers of a robot (or human) hand is generally called a grasp





- Precision grasp: object gripped by fingertips only



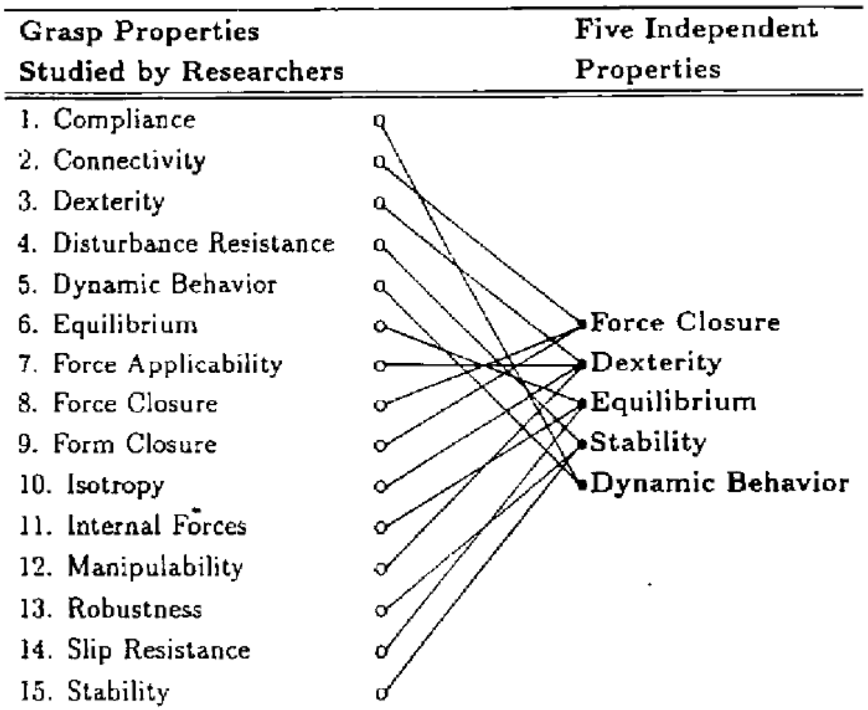
- Force-closure grasp is a grasp which is able to
  1. generate any external force that the grasped object may have to exert on an external body and
  2. counteract any external disturbing forces that may try to loosen the grip

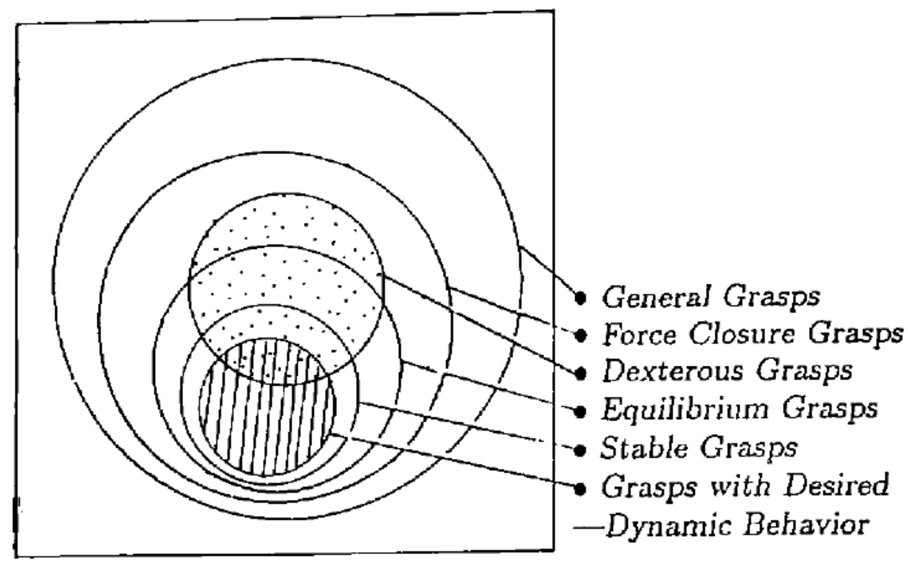
What properties are essential to grasps

- Researchers (Cutkosky 1989; Liu et al. 1989; Iberall 1987) have identified a multitude of properties that an articulated force-closure grasp must possess in order for it to be able to perform everyday tasks similar to those performed by human hands.

- Four mutually independent grasp properties:
  1. Dexterity: How should grasping fingers be configured?
  2. Equilibrium: How hard to squeeze the grasped object?
  3. Stability: How to remain unaffected by external disturbances?
  4. Dynamic behavior: How soft a grasp should be for a given task?

What properties are essential to grasps



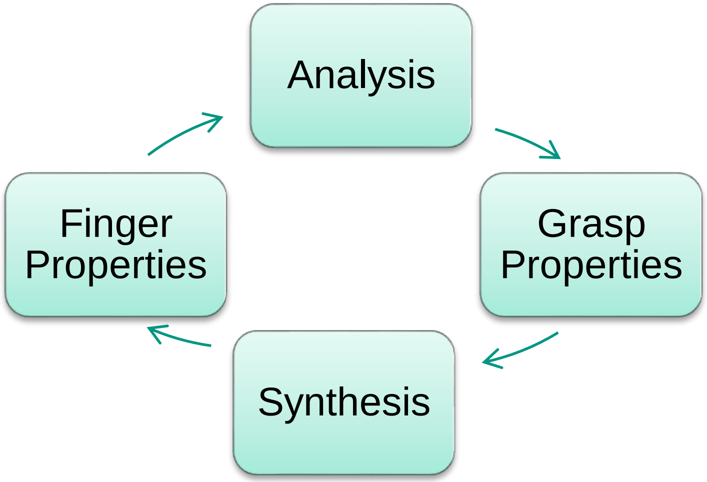


K.B. Shimoga, **Robot Grasp Synthesis Algorithms: A Survey**. The International Journal of Robotics Research June 1996 15: 230-266, doi:10.1177/027836499601500302

Grasp analysis and grasp synthesis

- Analysis means the study of grasp properties for a given set of finger properties.

- Synthesis means the determination of the required finger properties in order for the grasp to acquire some desired properties.



K.B. Shimoga, **Robot Grasp Synthesis Algorithms: A Survey**. The International Journal of Robotics Research June 1996 15: 230-266, doi:10.1177/027836499601500302

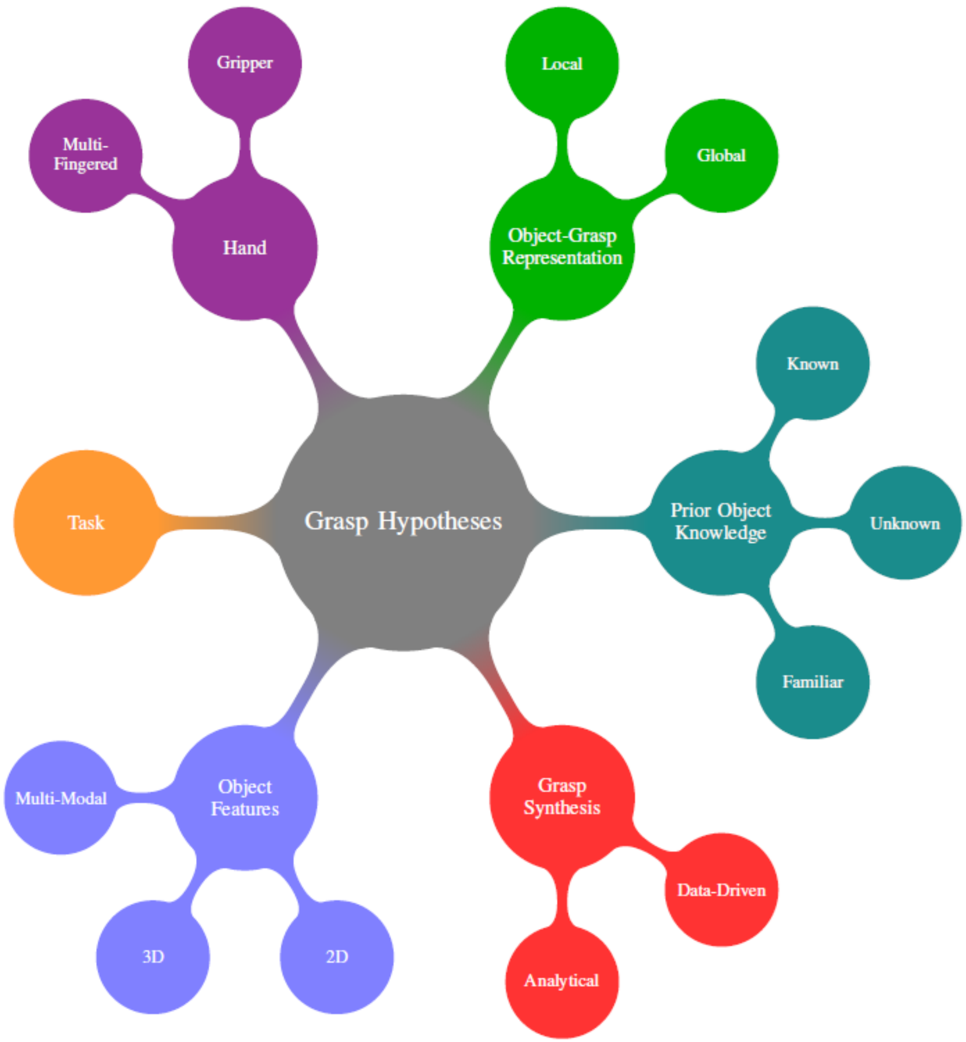
Grasp contacts

- Each point contact can be modelled as either
  - Frictionless point contact: Finger can only exert a force along the common normal at the point of contact
  - Frictional point contact: A contact that can transmit both a normal and tangential force
  - Soft contact: Allows the finger to exert a pure torsional moment about the common normal at the point of contact
- See Lecture “Robotic I”

What influences the generation of grasp hypotheses?

- Prior object knowledge
- Object-grasp representations
- Features of different modalities such as 2D or 3D vision or tactile sensors.
- Grasp synthesis
- Task
- Hand kinematics

Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014



Object classes for robot grasping

- Known objects (This is the domain of Grasp Planning!)
  - Known object geometry (i.e. we have a complete geometric object model)
  - Approach: Use various grasp planning methods (only for known objects!)
  - Hard
- “Familiar” objects
  - Class of object is known (e.g. “bottle”)
  - Approach: Reuse grasp knowledge from known class members for new object
  - Harder
- Unknown objects
  - No knowledge of the object
  - Challenges: Dealing with (incomplete) sensor data (stereo vision, RGB-D, laser scan, haptic data…), segmentation from the background, building a (partial) object model
  - Ideas: Multi sensor fusion, pushing the object, …
  - Hardest!

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  - Hardest!

Grasp planning is always about known objects!

Review papers on grasping

- Antonio Bicchi, Vijay Kumar, **Robotic grasping and contact: A review.** ICRA 2000
- Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014
  - Aspects that influence the generation of grasp hypotheses
  - Classification of the different approaches

Red: relevant for the exam

Grasping in Humans

Literature

- Umberto Castiello. ***The neuroscience of grasping,*** Nature Rev. Neurosci. 6, 726–736 (2005)

THE NEUROSCIENCE OF GRASPING

Umberto Castiello

Abstract | People have always been fascinated by the exquisite precision and flexibility of the human hand. When hand meets object, we confront the overlapping worlds of sensorimotor and cognitive functions. We reach for objects, grasp and lift them, manipulate them and use them to act on other objects. This review examines one of these actions — grasping. Recent research in behavioural neuroscience, neuroimaging and electrophysiology has the potential to reveal where in the brain the process of grasping is organized, but has yet to address several questions about the sensorimotor transformations that relate to the control of the hands.

Red: relevant for the exam

The neuroscience of grasping

The study of grasping was advanced by Napier's landmark work on PRECISION and POWER GRIPS.

- Precision grasp:A precision grasp is characterized by opposition of the thumb to one or more of the other fingers.
- Power grasp: In a power grasp, the fingers are flexed to form a clamp against the palm.

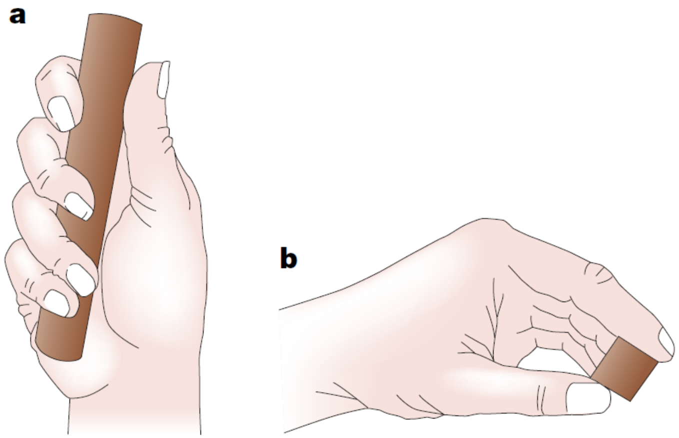


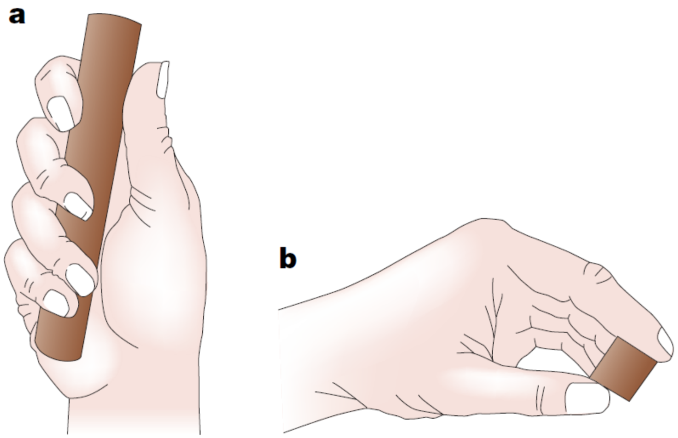
Figure 1 | **Examples of different grasps. a** | Power grip between thumb and all fingers. **b** | Precision grip between index finger and thumb. Modified, with permission, from REF. 10 © (1994) Elsevier Science.

Napier, J. R. *Hands* (George Allen & Unwin Ltd, London, 1980).
Napier, J. R. Studies of the hands of living primates. *Proc. Zool. Soc.* **134**, 647–657 (1960).
Napier, J. R. Prehensility and opposability in the hands of primates. *Symp. Zool. Soc.* **5**, 115–132 (1961).

The neuroscience of grasping

- Napier showed that despite the enormous variability in aspects of movement such as force, posture, duration and speed, the underlying control principles were amazingly elegant.

- These principles were based on the supposition that the intended activity determines what type of grasp is used for any given action (for example, grasping a pen to write involves a different grip from grasping it to put it in a box).



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1. Napier, J. R. *Hands* (George Allen & Unwin Ltd, London, 1980).
2. Napier, J. R. Studies of the hands of living primates. *Proc. Zool. Soc.* **134**, 647–657 (1960).
3. Napier, J. R. Prehensility and opposability in the hands of primates. *Symp. Zool. Soc.* **5**, 115–132 (1961).

The neuroscience of grasping

- Since these early studies, grasping has been widely investigated in humans and monkeys using various tasks and techniques.
- **Goal:** Integrate information from various domains to ascertain which neural circuits underlie grasping
- Paper's contributions:
  - Kinematics of grasping in humans and macaque monkeys.
  - Evidence that grasping requires several neural mechanisms, some of which are concerned with individual finger force and movement, and others that involve a specialized visuomotor system that encodes object features and generates the corresponding hand configurations.
  - Evidence from lesion and neuroimaging studies in humans is compared with neurophysiological studies in monkeys.
  - Although much of the work on grasping comes from monkeys, and this work has contributed to our understanding, caution is necessary when drawing homologies across species.
  - Factors that should be taken into account by neuroscientists in the quest to understand the neural bases of grasping.

The kinematics of grasping

- Kinematics consider movement in terms of position and displacement (angular and linear) of body segments, center of gravity, and acceleration and velocities of the whole body or segments of the body.
- The mechanics of grasping in humans and macaque monkeys vary depending on object attributes.
- Although the substantial differences in hand morphology between these two species are the focus of current debate, it is important to compare grasping in humans and monkeys because of the common practice of looking for homologies between the two species' brains.

The kinematics of grasping

- Jeannerod coded grasping in terms of changes in grip aperture - the separation between the thumb and the index finger.
  - During a reach-to-grasp movement, there is first a progressive opening of the grip with straightening of the fingers, followed by a gradual closure of the grip until it matches the object's size
  - The point in time at which the thumb-finger opening is the largest (maximum grip aperture) is a clearly identifiable landmark that
    - occurs within 60–70% of the duration of the reach and
    - is highly correlated with the size of the object

1. Jeannerod, M. in Attention and Performance IX (eds Long, J. & Baddeley, A.) 153–168 (Erlbaum, Hillsdale, 1981). **This paper was the first to characterize kinematically the reach-to-grasp movement in humans. This seminal work laid the foundation of much of our current understanding of grasping.**
2. Jeannerod, M. The timing of natural prehension movements. J. Mot. Behav. 16, 235–254 (1984).

The kinematics of grasping

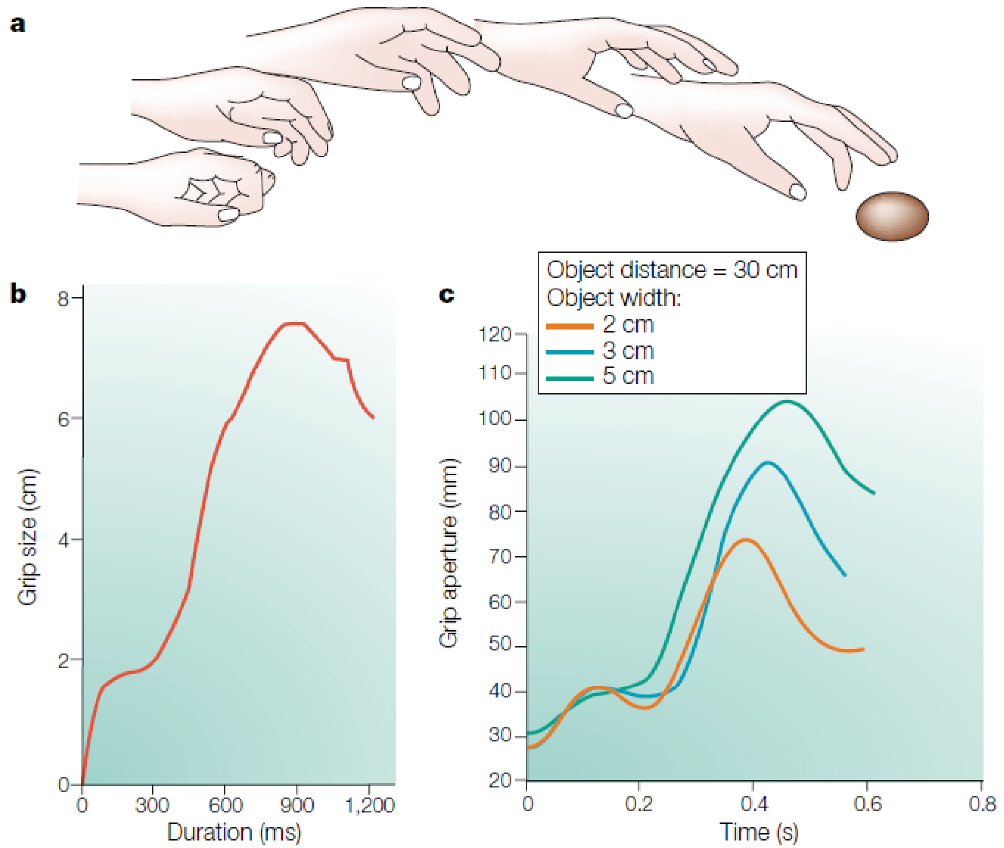


Figure 2 | **Kinematics of grasping. a** | The hand preshapes during its journey to the target object. **b** | Maximal grip aperture (distance between the tip of thumb and the tip of index finger) typically occurs within 70% of movement completion. **c** | Representation of traces demonstrating the scaling of maximum grip aperture with respect to object size. Panels **a** and **b** modified, with permission, from REF. 12 © (1984) Heldref Publications. Panel **c** modified, with permission, from REF. 13 © (1991) Springer.

Kinematics of grasping in monkeys and humans

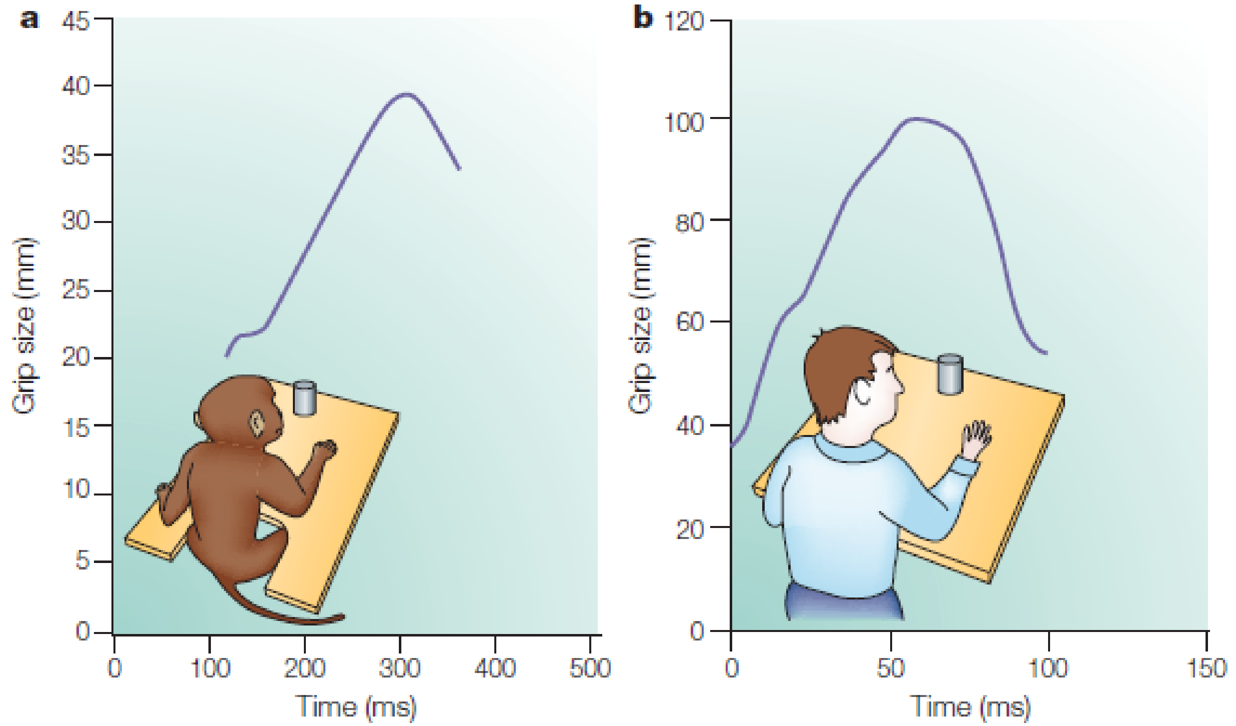
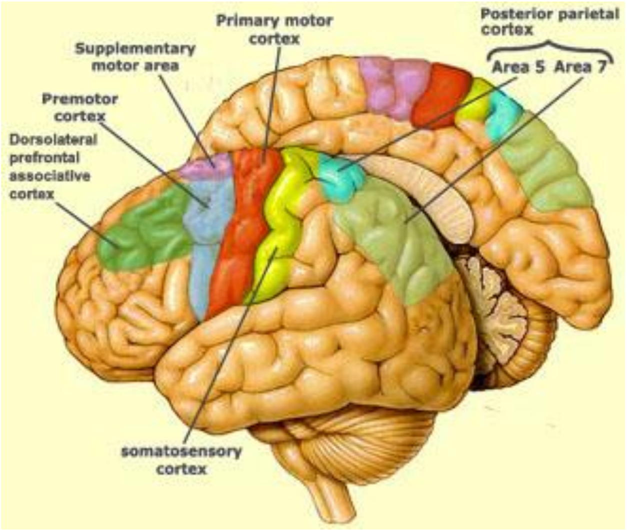


Figure 3 | **Comparison of the kinematics of grasping in monkeys and humans: effect of size.** Grip size in (**a**) a macaque monkey and (**b**) a human subject. In both species, the grasping component is characterized by a grip size that increases up to a maximum and then decreases towards the end of the movement. The macaque data are presented in absolute time, whereas those for the human participants are presented in normalized time, as a percentage of movement duration. The object diameter was 15 mm. Modified, with permission, from REF. 44 © (2000) Elsevier Science.

The neurophysiology of grasping

- Study of single cells in the monkey brain.
- Three specific areas relating to grasping have been identified in the monkey cortex
  - the primary motor cortex (F1),
  - the premotor cortex (PML/F5)
  - and the anterior intraparietal sulcus (AIP).
- In terms of neural mechanisms, performing a successful grasping action depends primarily on the integrity of the primary motor cortex (F1).
  - In monkeys, lesions of this area produce a profound deficit in the control of individual fingers and consequently disrupt normal grasping



Neural circuits for grasping in monkeys and humans

- Given the wealth of evidence for a grasping circuit involving several areas in the monkey brain, the natural question is whether a similar circuit exists in humans.

- For ethical reasons, invasive physiological recording of brain activity is rarely possible in humans. Nonetheless, considerable progress has been made towards understanding the neural substrates of grasping in humans, mainly from studies of patients with brain damage and neuroimaging experiments.

The neuropsychology of grasping

- Jeannerod found that in reaching out to grasp an object, the finger grip aperture of patients with optic ataxia was abnormally large, and the usual correlation between maximum grip aperture and object size was missing.

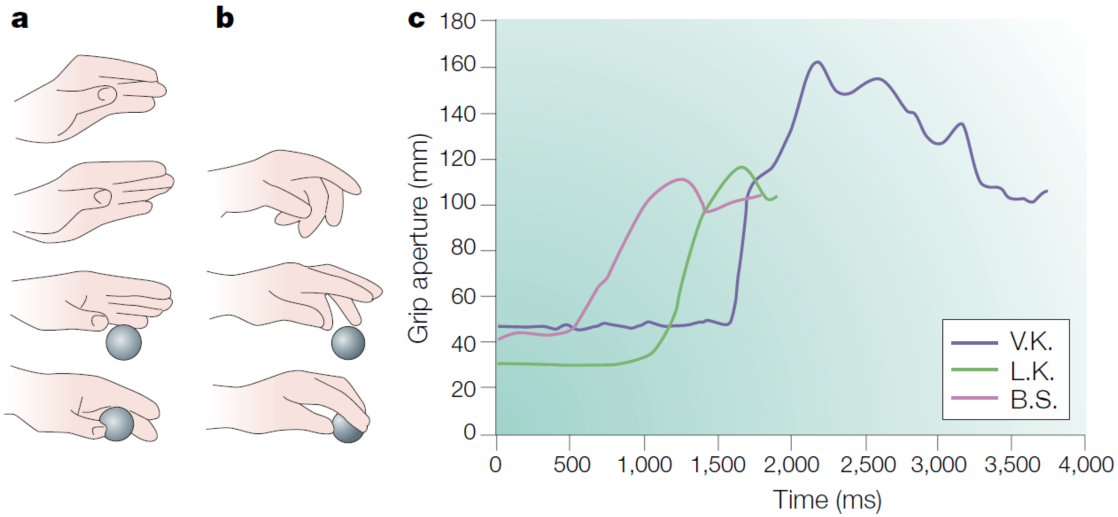
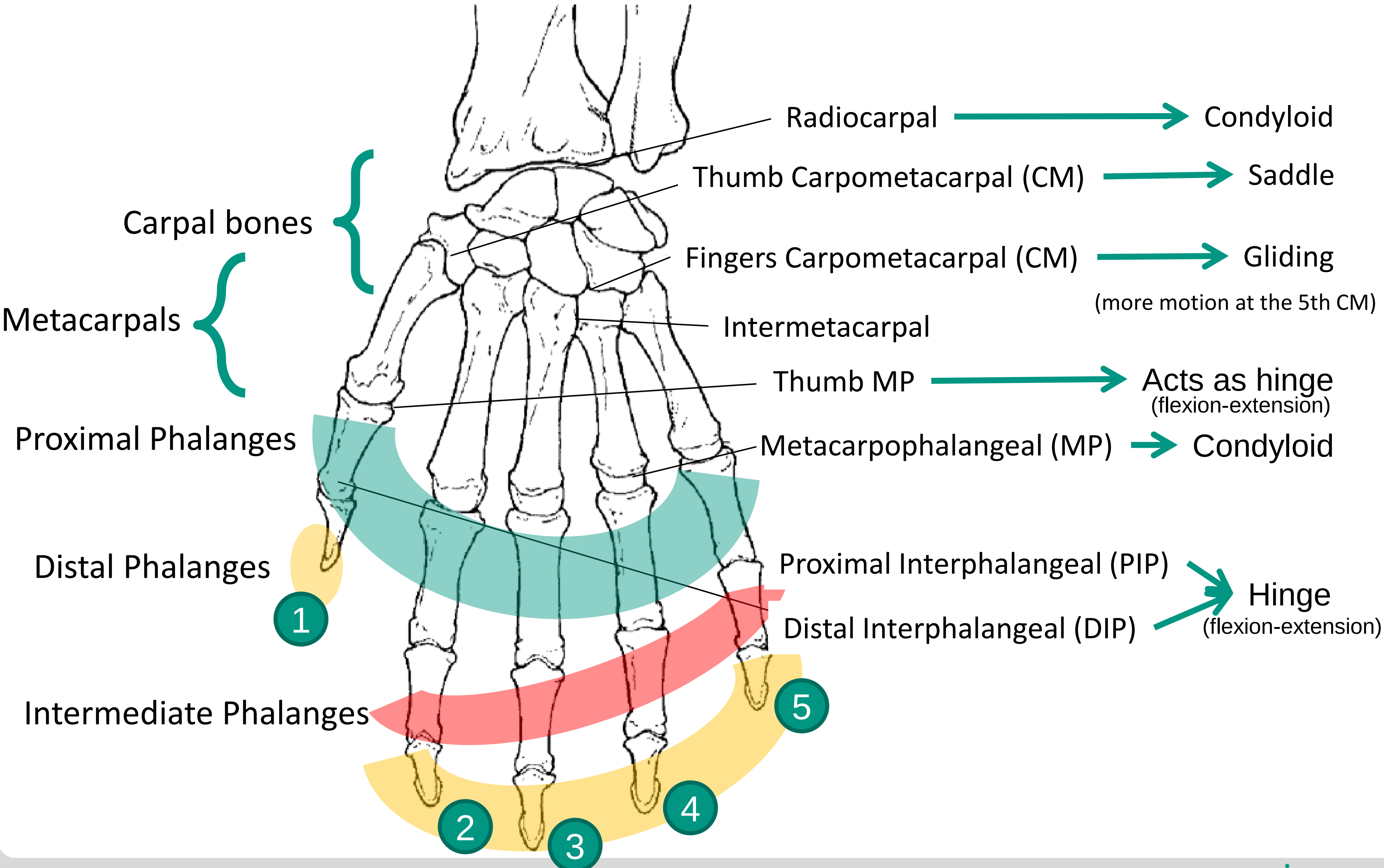


Figure 6 | **Grip aperture profiles of patients with brain damage.** Comparison of the pattern of finger grip in a patient, 'Biz', with optic ataxia during reaching with the affected hand (**a**) and the normal hand (**b**). **c** | Comparison of the abnormal pattern of finger grip in a patient, V.K., with the pattern of finger grip of two neurologically healthy participants (L.K. and B.S.). Panels **a** and **b** modified, with permission, from REF. 79 © (1986) Elsevier Science. Panel **c** modified, with permission, from REF. 80 © (1991) Elsevier Science.

Optic ataxia is classically considered to be a specific disorder of the visuomotor transformation caused by posterior parietal lesions, in particular, lesions of the superior parietal lobe (SPL).

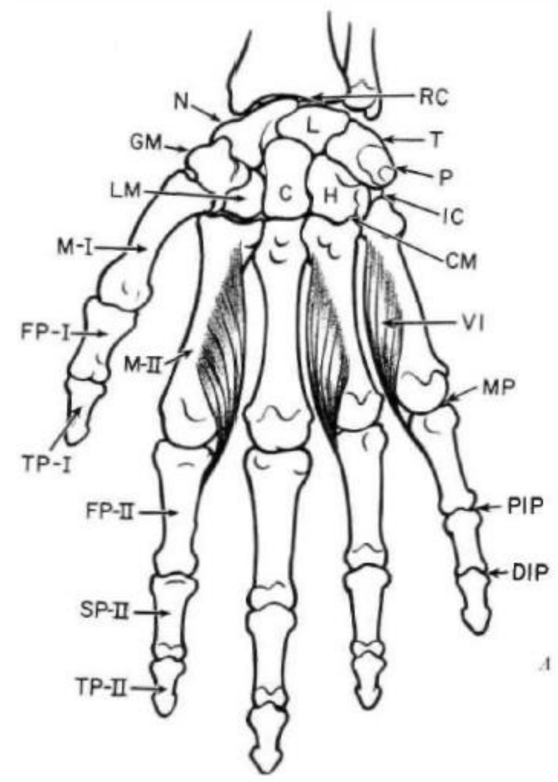
Human Hand Models

Hand : Bones and joints



Anatomy of the human hand

- 27 bones
- 27 DoF (total)
  - 3 DoF flexion/extension type per finger
  - 1 DoF abduction/adduction type per finger
  - 5 DoF thumb:
    - 3 DoF flexion/extension type
    - 2 DoF abduction/adduction type
  - 6 DoF at the carpus (palm)



U. Schmidt, Hans-Martin; Lanz. Chirurgische Anatomie der Hand. Stuttgart, New York, 2003. Georg Thieme Verlag

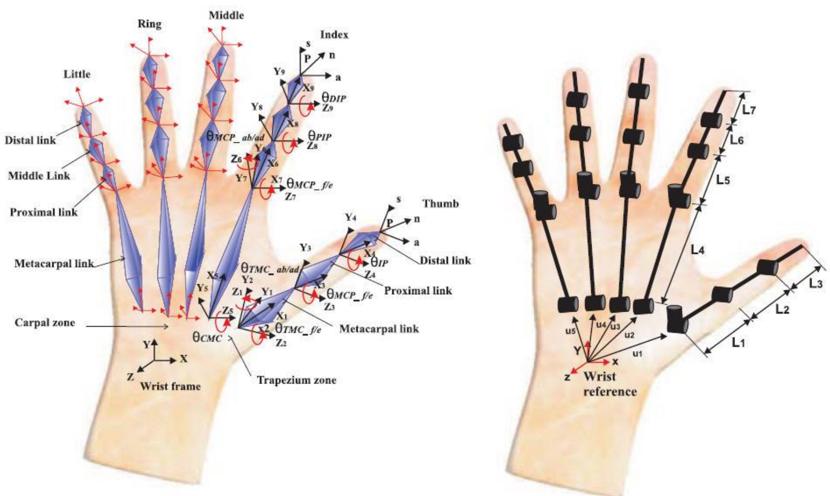
Human hand models in the literature

- Large variety of human hand models
  - Different kinematic models
  - Varying numbers of DoF
  - Depending on the purpose
  - Not only in robotics but also in computer vision, Human-Computer interaction, biomedical engineering, …
- Different applications
  - Grasp planning and analysis: More complex thumb kinematics useful
  - Prosthetics hands
  - Understanding human grasping
  - Tracking (usually no intrinsic DoFs in the palm necessary)
- Always trade-off between requirements for intended use and complexity

Human hand models

Cobos et al., 2008

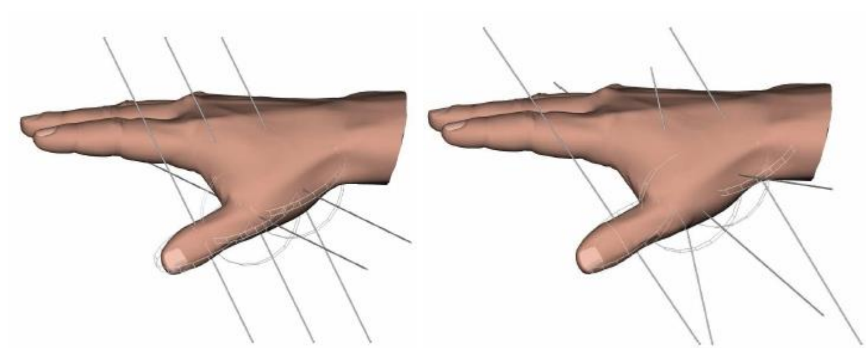
- 24 DoF (total)
- 1 DoF carpometacarpal (CMC) joint per finger
- 4 DoF thumb



S. Cobos, et al. Efficient human hand kinematics for manipulation tasks. Intelligent Robots and Systems 2008, pages 2246-2251, Sept. 2008.

Miller et al., 2005

- 21 DoF (total)
- 5 DoF thumb, 2 versions:
  - perpendicular joint axes
  - non-perpendicular joint axes

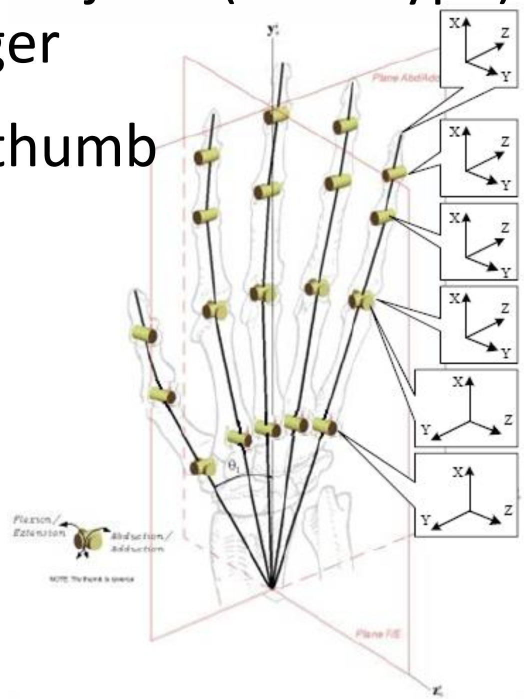


A. Miller, et al.: From Robotic Hands to Human Hands: A Visualization and Simulation Engine for Grasping Research. Industrial Robot: An International Journal,, 2005

Human hand models

Du and Charbon 2007

- 24 DoF (total)
- 1 DoF TM joint (twist type) per finger
- 4 DoF thumb



Kuch and Huang 1994

- 23 DoF (total)
- 2 DoF at the palm:
  - at the base of ring and pinky metacarpals
- 5 DoF thumb

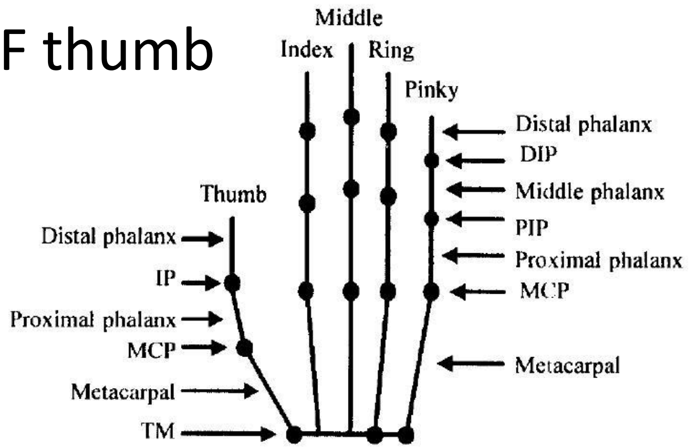


Figure 1. Notational diagram for the human hand.

H. Du and E. Charbon. 3d hand model Fitting for virtual keyboard system. In WACV '07: Proceedings of the Eighth IEEE Workshop on Applications of Computer Vision

J. Kuch, T. S. Huang: Human Computer Interaction via the Human Hand: A Hand Model. Conference Record of the 28th Conference on Signals, Systems and Computers 1994

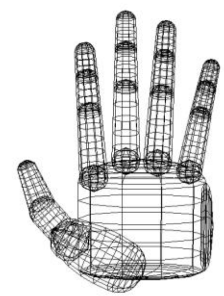
Human hand models

Pollard and Zordan 2005

- 19 ball joints for a total of 57 DoF
- for motion capturing use

Stenger et al. 2001

- 20 intrinsic DoF (total)
- 4 DoF per finger
- 4 DoF thumb
- no DoF at the palm
- Used for hand tracking
- Hand joints represent segments in the model

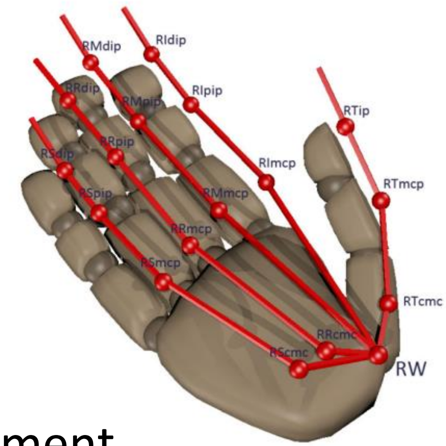


N.S. Pollard, V.B. Zordan: Physically based grasping control from example. Proceedings of the 2005 ACM SIGGRAPH/Eurographics symposium on Computer animation, pages 311-318

B. Stenger, P. R. S. Mendonca, and R. Cipolla. Model based 3D tracking of an articulated hand. In Proc. CVPR, volume II, pages 310–315, Kauai, HI, December 2001.

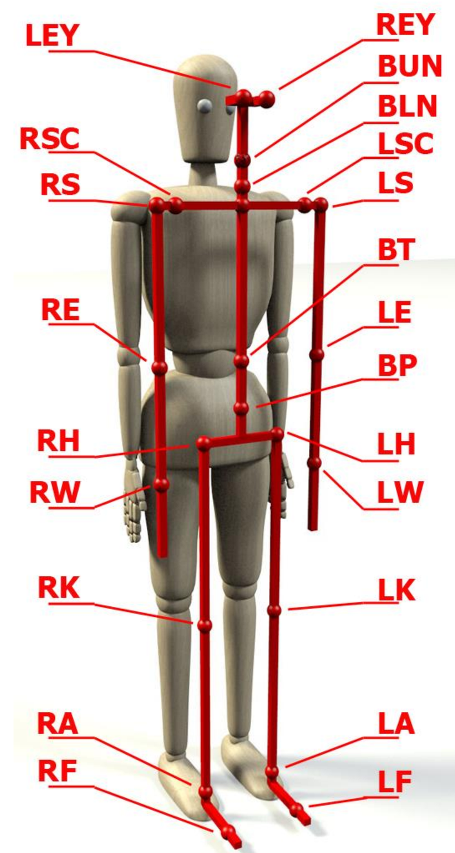
Karlsruhe human hand model (MMM model)

- Kinematics
  - 23 DoF



- Anthropometric data
  - Anatomically correct finger segment lengths depend on total hand length
  - Based on data from (Buchholz et al. 1992)

- Part of the MMM at H²T
  https://gitlab.com/groups/mastermotormap



Literature: Human hand models

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2. S. Cobos, M. Ferre, M. Sanchez Uran, J. Ortego, and C. Pena. Efficient human hand kinematics for manipulation tasks. Intelligent Robots and Systems 2008, pages 2246-2251, Sept. 2008.

3. H. Du and E. Charbon. 3d hand model fitting for virtual keyboard system. In WACV '07: Proceedings of the Eighth IEEE Workshop on Applications of Computer Vision, page 31, Washington, DC, USA, 2007. IEEE Computer Society.

4. U. Schmidt, Hans-Martin; Lanz. Chirurgische Anatomie der Hand. Stuttgart, New York, 2003. Georg Thieme Verlag.

5. J. Kuch, T.S. Huang: Human Computer Interaction via the Human Hand: A Hand Model. Conference Record of the 28th Asilomar Conference on Signals, Systems and Computers 1994, pages 1252-1256

6. A. Miller, P. Allen, V. Santos, F. Valero-Cuevas: From Robotic Hands to Human Hands: A Visualization and Simulation Engine for Grasping Research. Industrial Robot: An International Journal, Volume 32, 2005

7. N.S. Pollard, V.B. Zordan: Physically based grasping control from example. Proceedings of the 2005 ACM SIGGRAPH/Eurographics symposium on Computer animation, pages 311-318

8. B. Stenger, P. R. S. Mendonca, and R. Cipolla. Model based 3D tracking of an articulated hand. In Proc. CVPR, volume II, pages 310–315, Kauai, HI, December 2001.

9. F. J. Valero-Cuevas, M. E. Johanson, and J. D. Towles. Towards a realistic biomechanical model of the thumb: the choice of kinematic description may be more critical than the solution method or the variability/uncertainty of musculoskeletal parameters. Journal of Biomechanics, 36(7):1019 - 1030, 2003.

Grasping Taxonomies

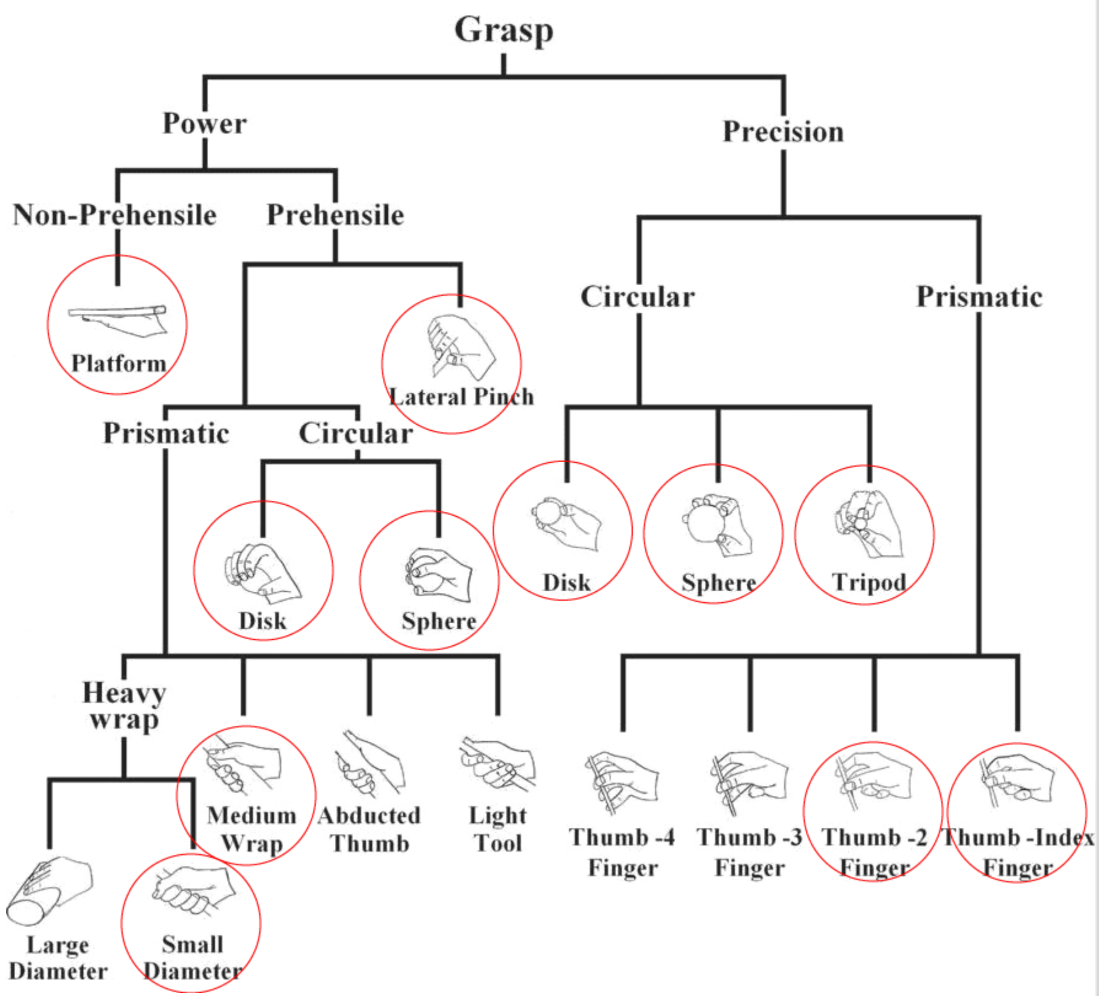
Why a taxonomy?

- Benchmark to test robot hand abilities
- Simplify grasp synthesis
- Inspire hand design
- Optimization of synergies: Formulation of dexterity/functionality as number of achievable grasps for maximization
- Guide autonomous grasp selection

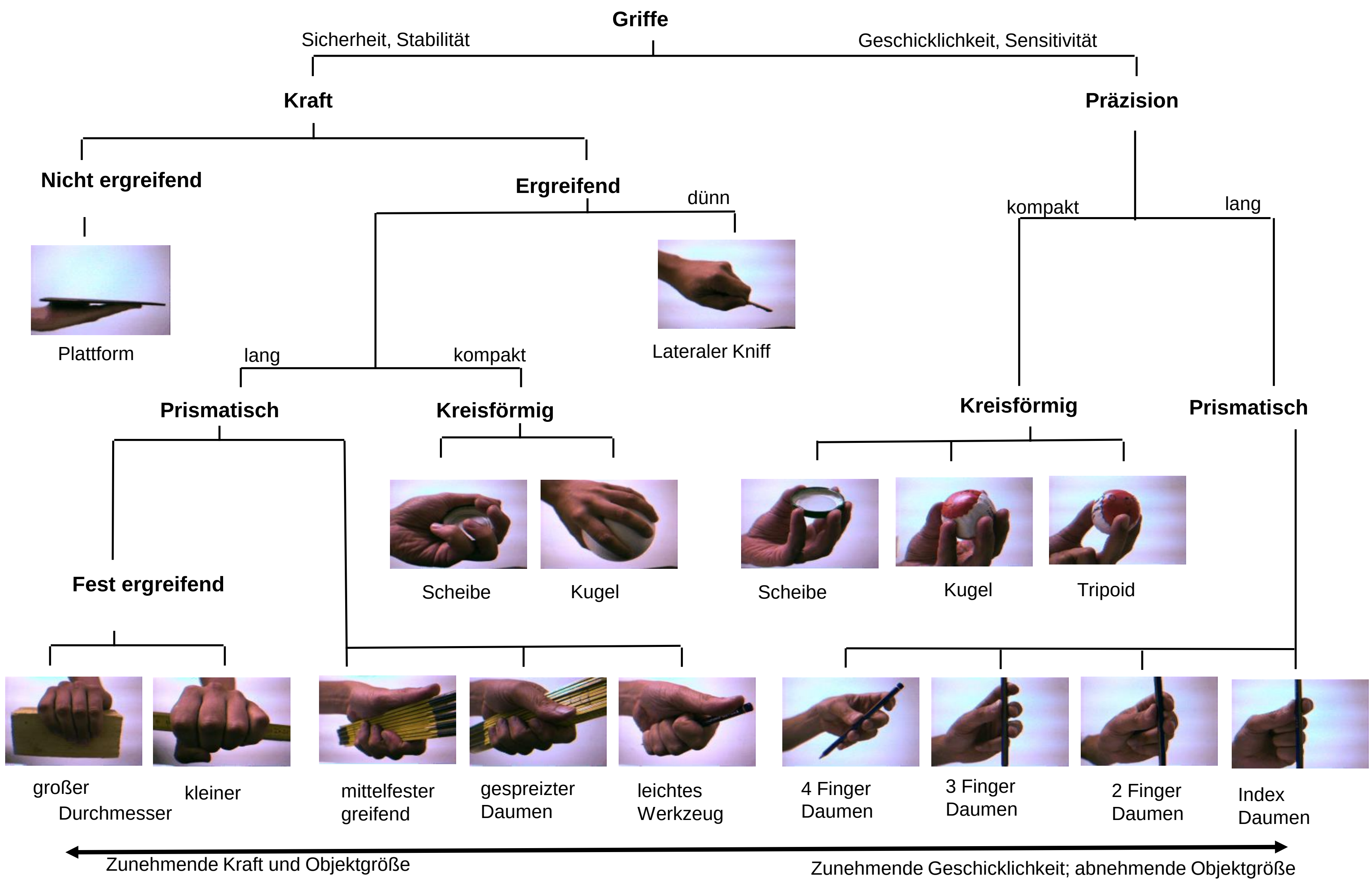
Grasp Taxonomies (*Cutkosky)*

- Power and Precision grasps
- Obtained by observing machinists during their work
- Focus on using tools in a workshop

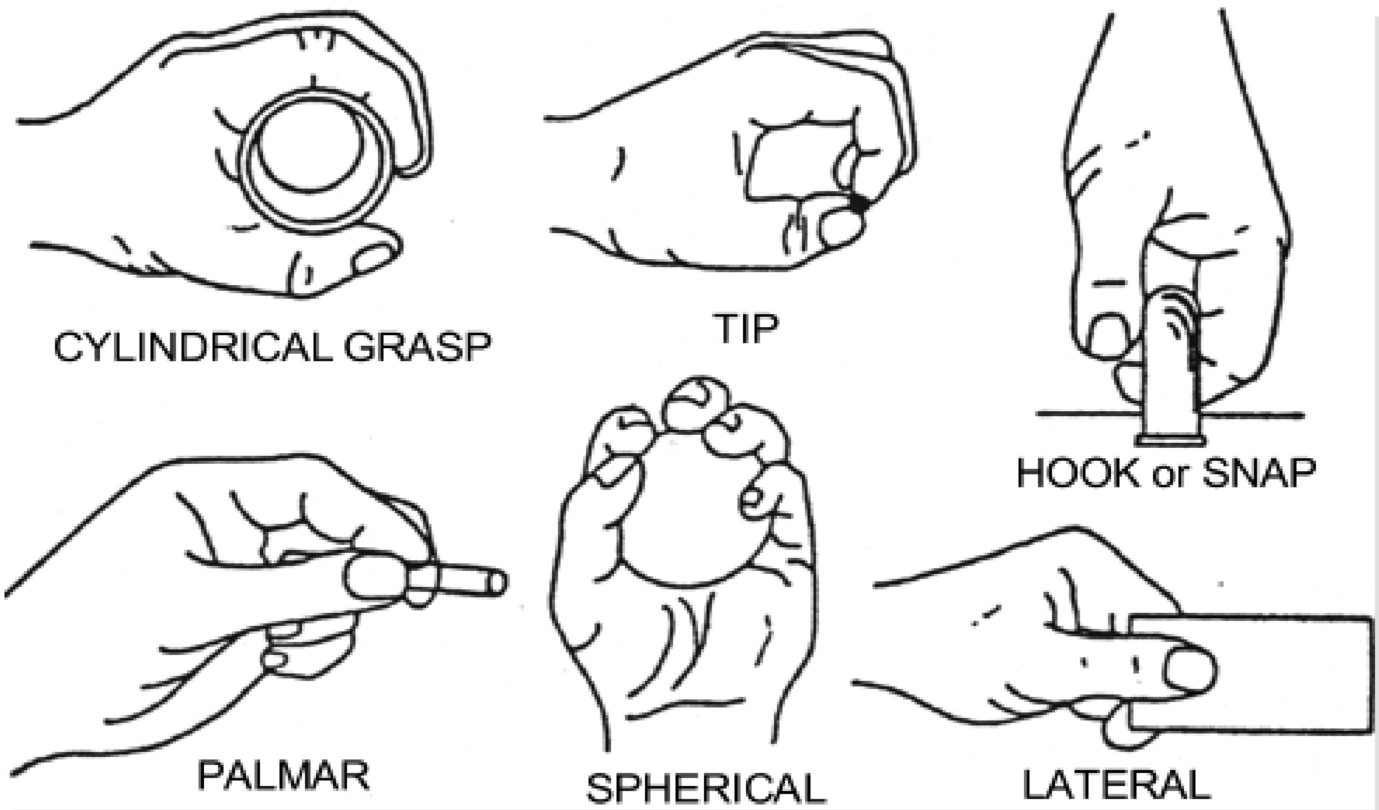
Mark Cutkosky, *On Grasp Choice, Grasp Models, and the Design of Hands for Manufacturing Tasks*. IEEE Transactions on Robotics and Automation, vol. 5, no. 3, pp. 269 – 279, 1989



Cutkosky Grifftaxanomie



Typical grasp motion of daily life



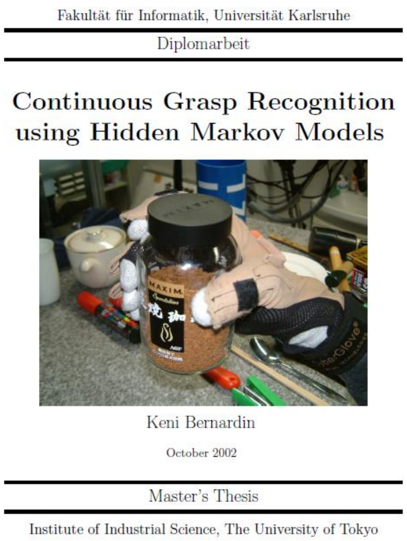
A. D. Keller, C. L. Taylor and V. Zahm: Studies to determine the functional requirements for hand & arm prostheses, Dept. of Engr., UCLA., CA, 1947

Kamakura Taxonomy

N. Kamakura, M. Ohmura, H. Ishii, F. Mitsubosi, and Y. Miura. Patterns of static prehension in normal hands. In Amer. J. Occup. Ther., vol. 34, pp. 437–445, 1980

N. Kamakura. Te no ugoki, Te no katachi (Japanese). Ishiyaku Publishers, Inc., Tokyo, Japan, 1989.

Keni Bernardin, Master Thesis, University of Karlsruhe


Fakultät für Informatik, Universität Karlsruhe

Diplomarbeit

Continuous Grasp Recognition using Hidden Markov Models

Keni Bernardin

October 2002

Master's Thesis

Institute of Industrial Science, The University of Tokyo

Kamakura Taxonomy

- The taxonomy considers
  1. purpose of a grasp
  2. hand shape
  3. contact points with objects

- General enough to be used for most manipulation tasks

Table 4.1: Grasp Taxonomy by Kamakura

Category	Class	Notation
Power Grips	Power Grip-Standard Type	PoS
	Power Grip-Hook Type	PoH
	Power Grip-Index Extension Type	PoI
	Power Grip-Extension Type	PoE
	Power Grip-Distal Type	PoD
Mid-Power-Precision Grips	Lateral Grip	Lat
	Tripod Grip-Standard Type	Tpd
	Tripod Grip-Variation I	TVI
	Tripod Grip-Variation II	TVII
Precision Grips	Parallel Mild Flexion Grip	PMF
	Circular Mild Flexion Grip	CMF
	Tip Grip	Tip
	Parallel Extension Grip	PE
Thumbless Grips	Adduction Grip	Add

Kamakura Taxonomy

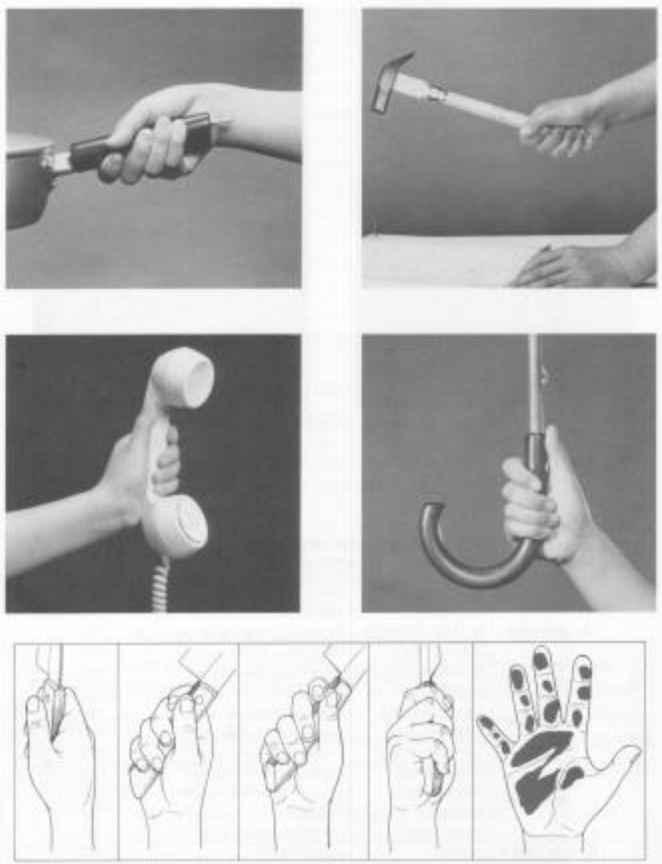


Figure 4.2: The Power Grip Standard Type (PoS)

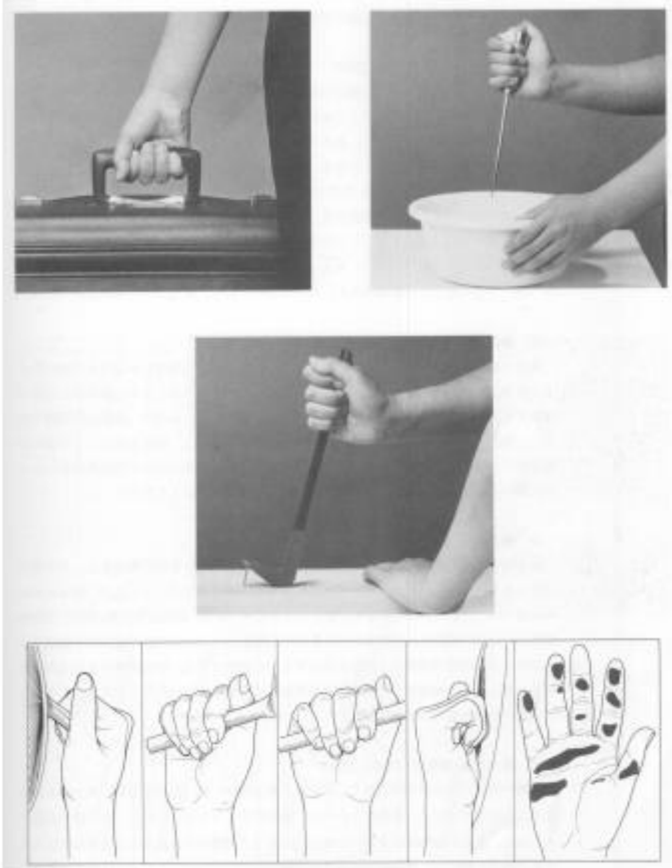


Figure 4.3: The Power Grip Hook Type (PoH)

Kamakura Taxonomy

Figure 4.4: The Power Grip Index Extension Type (PoI)

Figure 4.5: The Power Grip Extension Type (PoE)

Kamakura Taxonomy

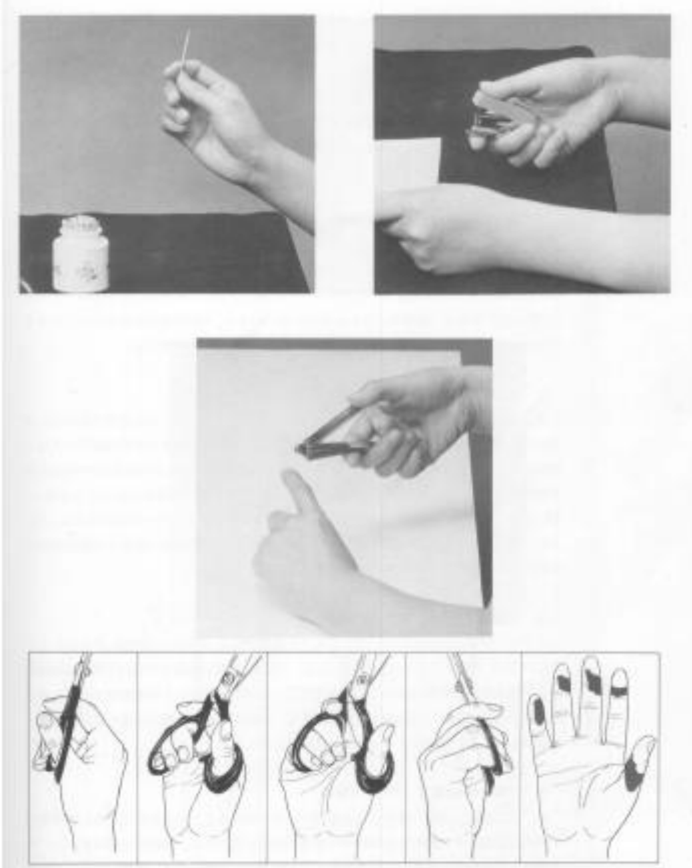


Figure 4.6: The Power Grip Distal Type (PoD)

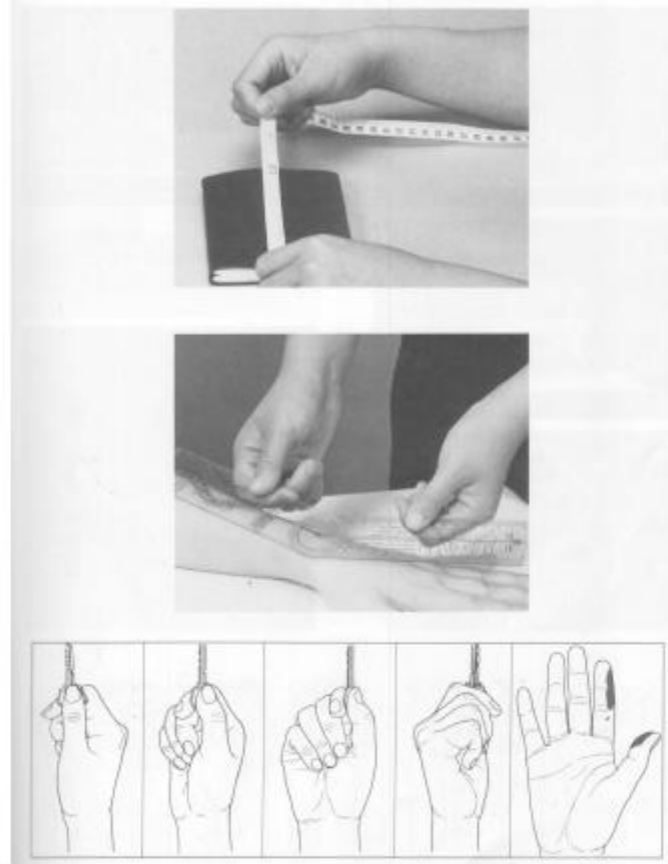


Figure 4.7: The Lateral Grip (Lat)

Kamakura Taxonomy

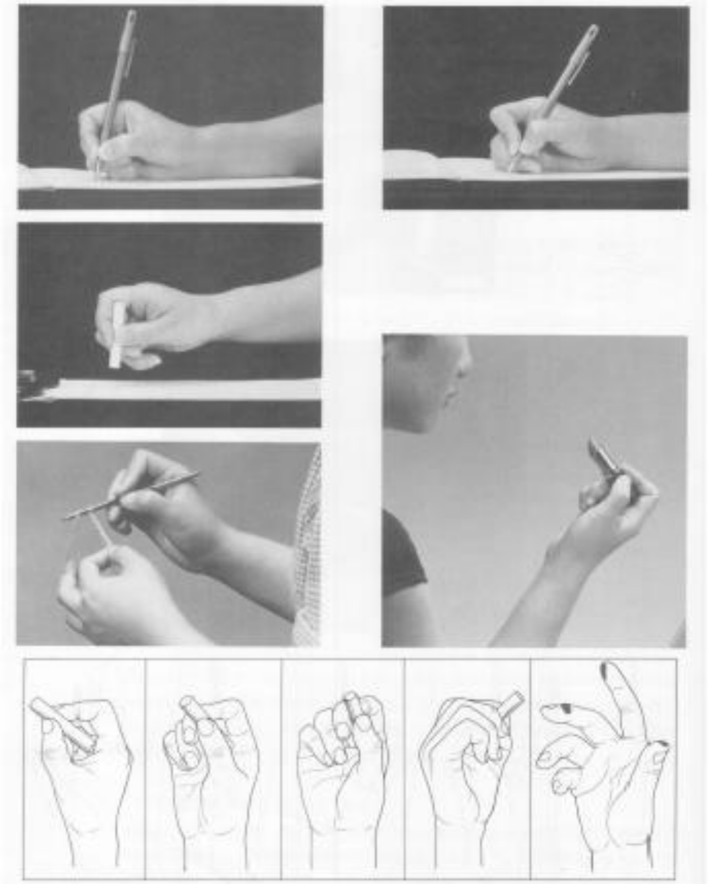


Figure 4.8: The Tripod Grip (Tpd)

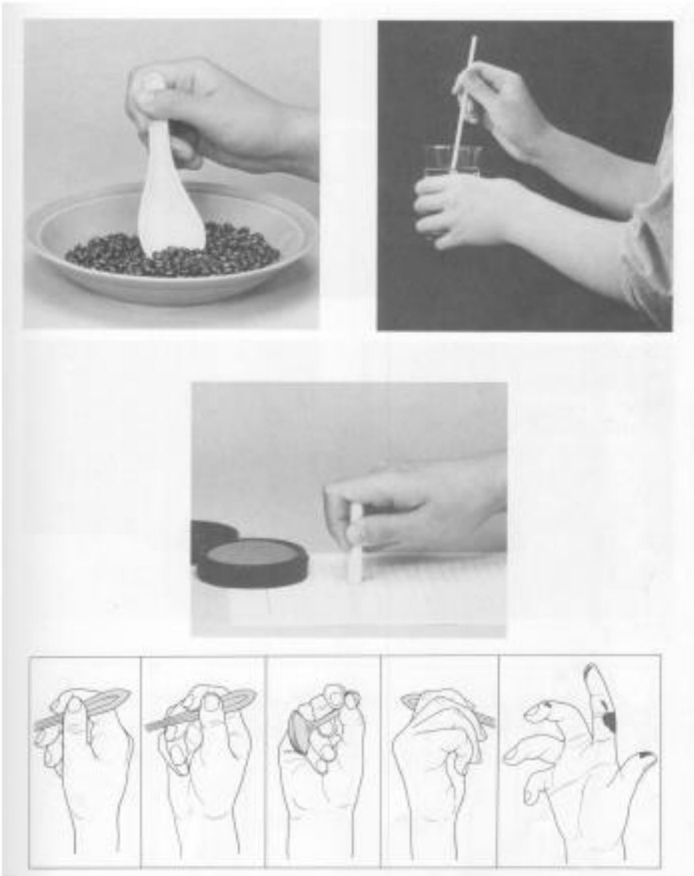


Figure 4.9: The Tripod Grip Variation I (TVI)

Kamakura Taxonomy

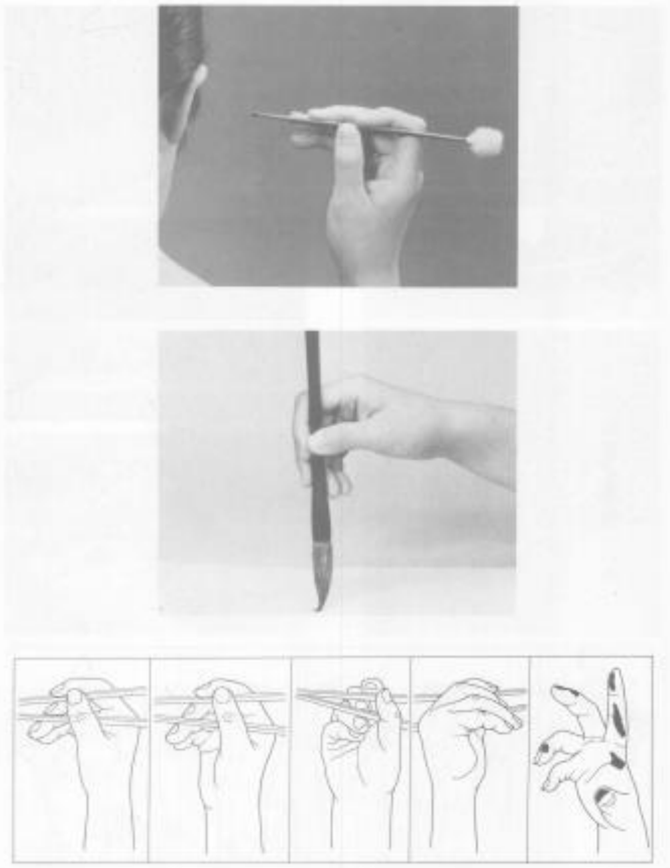


Figure 4.10: The Tripod Grip Variation II (TVII)

Figure 4.11: The Parallel Mild Flexion Grip (PMF)

Kamakura Taxonomy

Figure 4.12: The Circular Mild Flexion Grip (CMF)

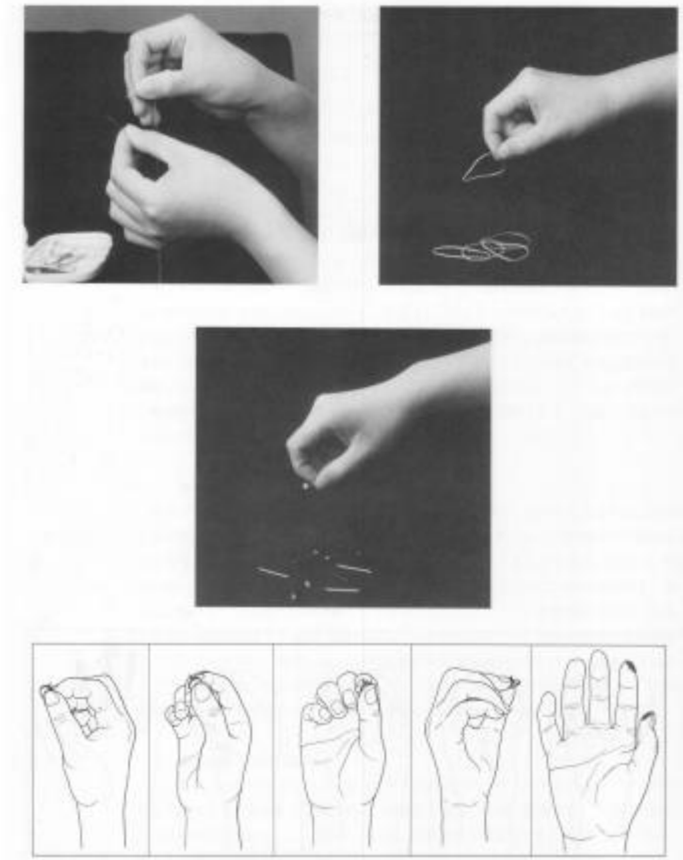


Figure 4.13: The Tip Grip (Tip)

Kamakura Taxonomy

Figure 4.14: The Parallel Extension Grip (PE)

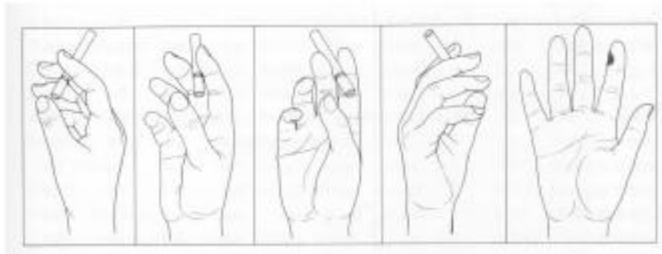
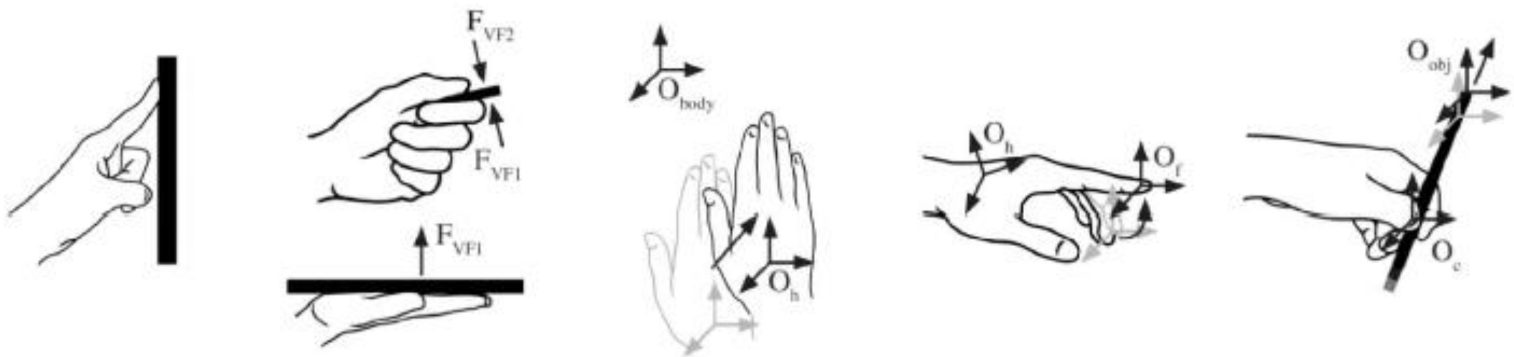


Figure 4.15: The Adduction Grip (Add)

Bullock Taxonomy

- Important terms in the taxonomy



Contact
Hand is touching an external object or the environment.

Prehensile
Action of hand on object must be described with more than one virtual finger.

Motion
Any part of the hand moves relative to body fixed frame.

Within Hand
Points on the hand are moving relative to the hand base frame.

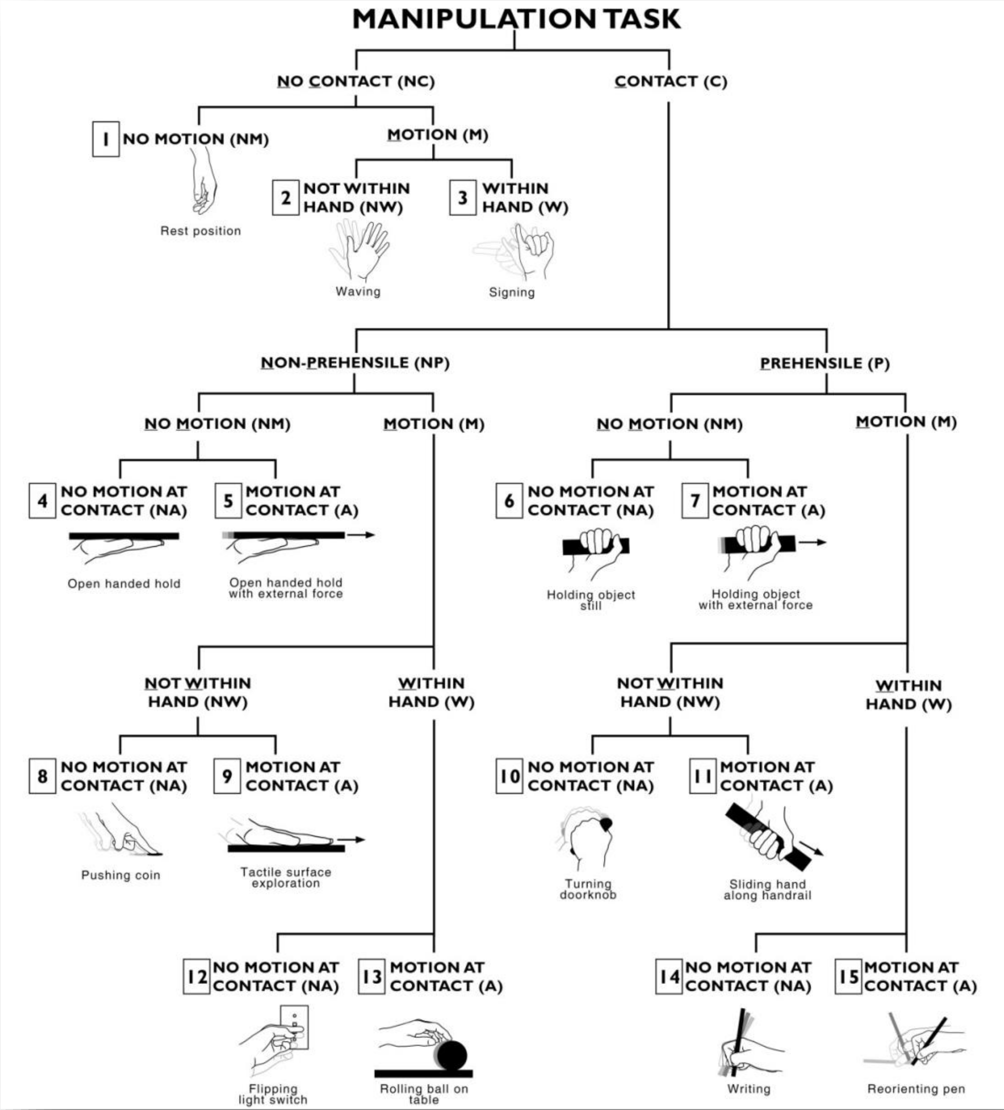
Motion at contact
Object reference frame moves relative to contact point frame(s).

Bullock, I.M.; Ma, R.R.; Dollar, A.M., "A Hand-Centric Classification of Human and Robot Dexterous Manipulation," *IEEE Transactions on Haptics*, 6(2):129-144, 2013

Bullock Taxonomy

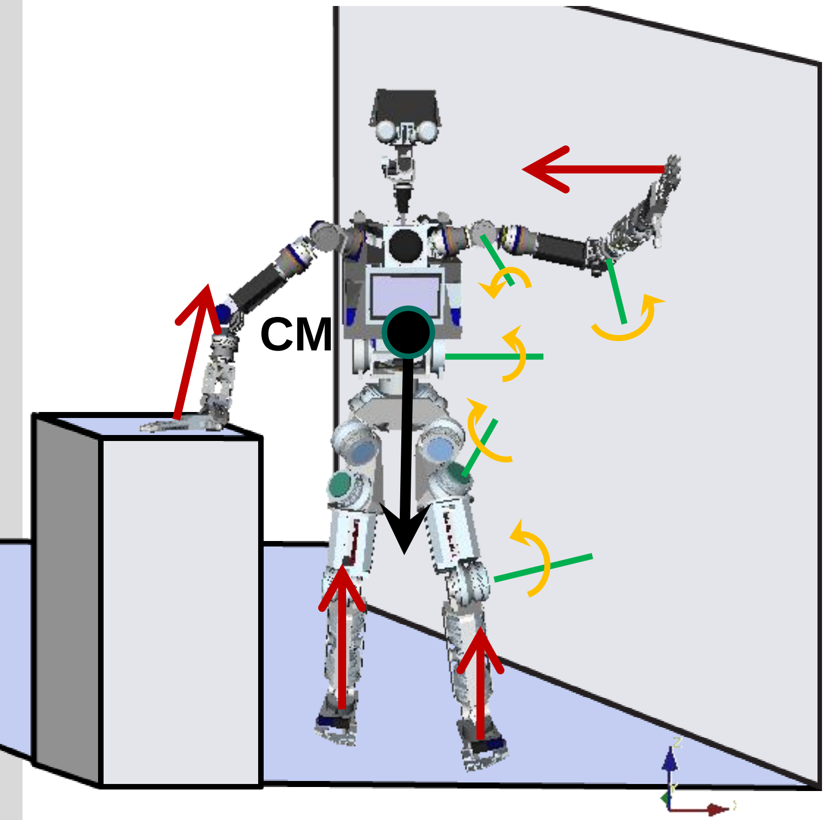
- Hand-centric and motion-centric manipulation classification

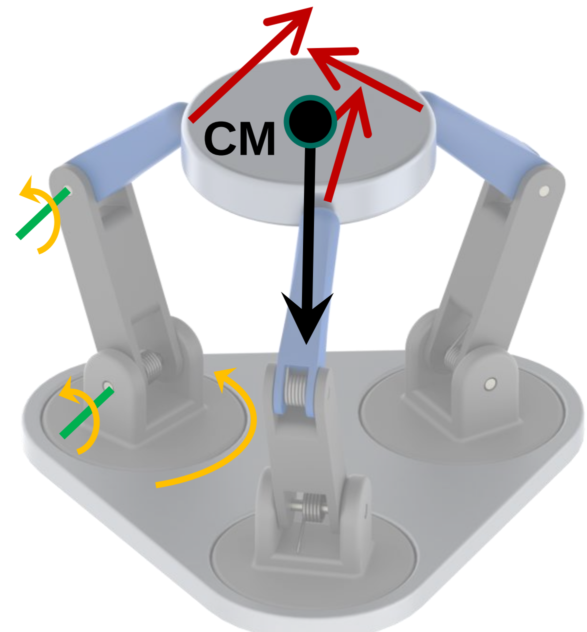
Bullock, I.M.; Ma, R.R.; Dollar, A.M., "A Hand-Centric Classification of Human and Robot Dexterous Manipulation," *IEEE Transactions on Haptics*, 6(2):129-144, 2013



Duality of grasping and balancing

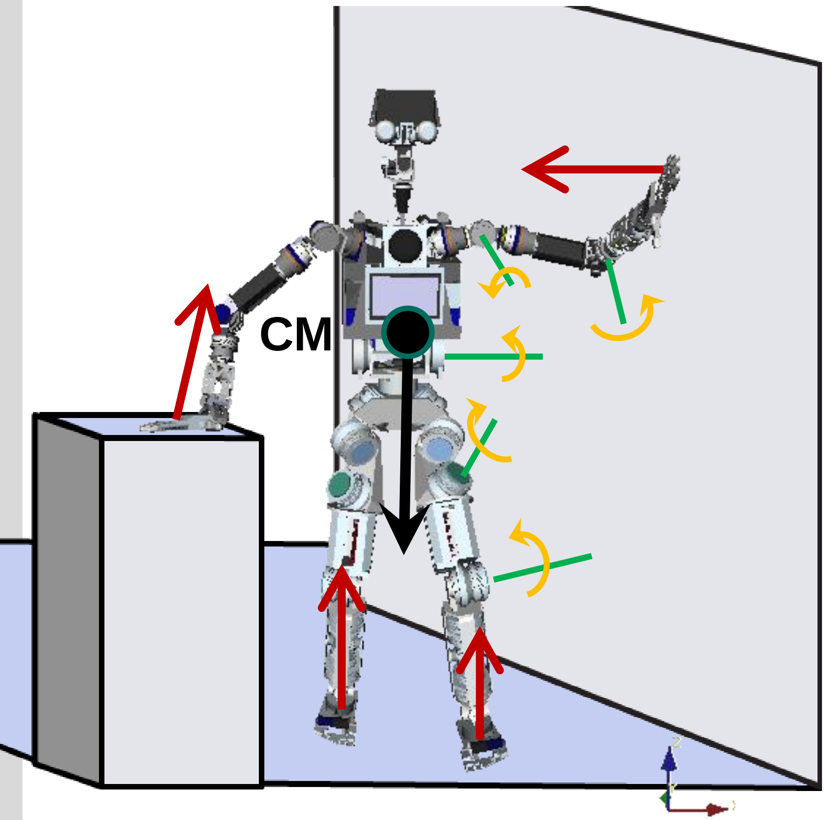
Equilibrium is reached by balancing similar sets of forces





Ground reaction forces	⟷	Fingertip forces
Weight of the body (CM)	⟷	Weight of the object (CM)
Torques on the joints	⟷	Torques on the joints

Duality of grasping and balancing



Concepts of grasping can be applied to loco-manipulation

$$\mathbf{G}^T\mathbf{T} = \mathbf{J}_H\dot{\Theta}$$
$$\mathbf{J}_H^T\lambda_f = \tau$$
$$-\mathbf{G}\lambda_f = \mathbf{W}$$
$$\lambda_f \in \mathscr{F}$$

Balance $\Longleftrightarrow$ Stable grasp

Step planning $\Longleftrightarrow$ Grasp synthesis

Duality of grasping and balancing

Selection of support pose	⟷	Grasp selection
Selection of contact points	⟷	Grasp synthesis
Classification of support pose possibilities	⟷	**Grasping taxonomies**

J. Borràs and T. Asfour, A Whole-Body Pose Taxonomy for Loco-Manipulation Tasks, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 1578 - 1585, October, 2015

Red: relevant for the exam

Whole-body poses in loco-manipulation tasks

Given: humanoid, task and scene and its affordances:

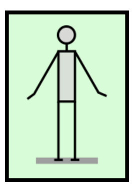
- How many poses can be realized?
- Which pose should be selected ?
- How to realize it? planning, control

→ Taxonomy

The whole-body can adopt many poses for balancing

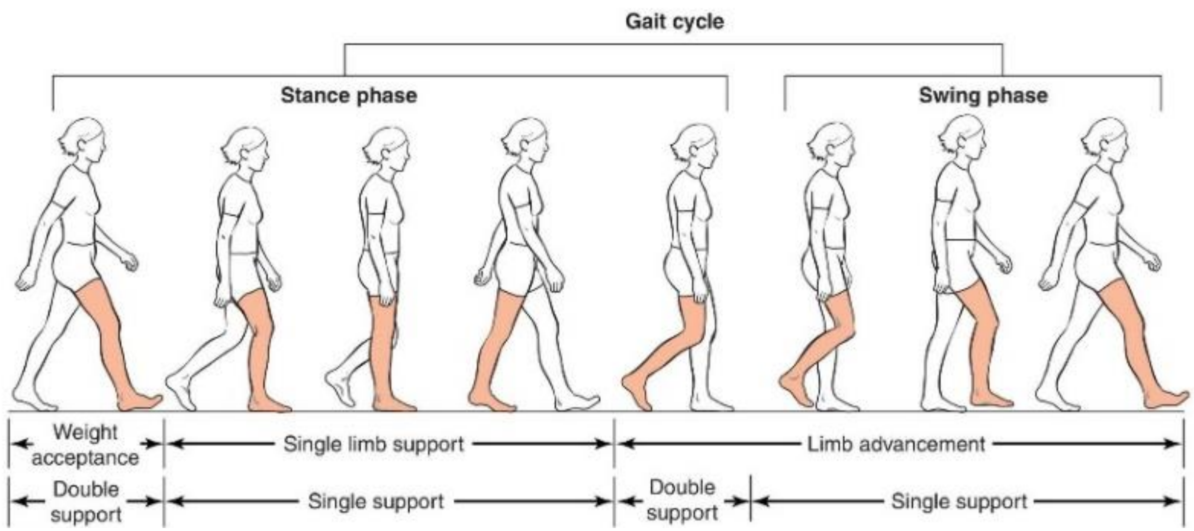
Classic postures:

Single
foot support



Double
foot support

Postures and their transitions are very well studied



Whole-body poses in loco-manipulation tasks

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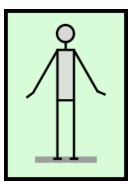
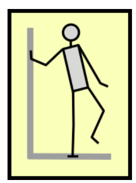


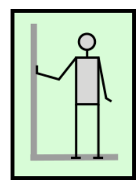
Double
foot support

Postures and their transitions are very well studied

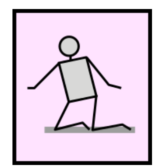
Other possible combinations:



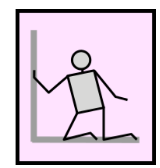
1 Hand
1 Foot



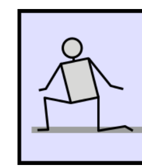
1 Hand
2 Feet



Double
knee support

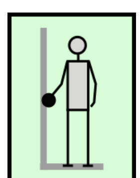


1 Hand
2 Knees

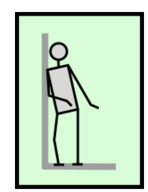


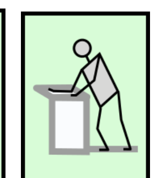
1 Foot
1 Knee

Considering other types of contacts:



Double foot support with hold (hand grasping a handle)

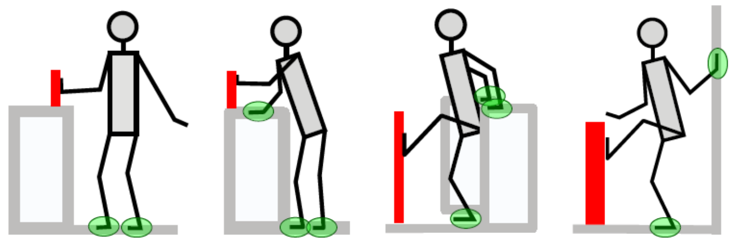




Arm contacts

Towards a taxonomy of whole body support poses

- Support pose: defined by contacts that provide balance support

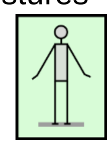


We ignore contacts with manipulation objects

- Criteria for classification:
  - **Number of contacts**: Relevant for balance conditions/control
  - **Type of contacts**: Determine the mobility (DoFs) and the transmission of contact forces
  - **Possible transitions**: We only allow one contact change at a time.
- Possible poses beyond walking

Classic postures

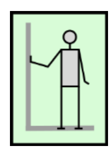
Single foot support



Double foot support

How many combinations are possible?

1 Hand 1 Foot



1 Hand 2 Feet

Double knee support

1 Hand 2 Knees

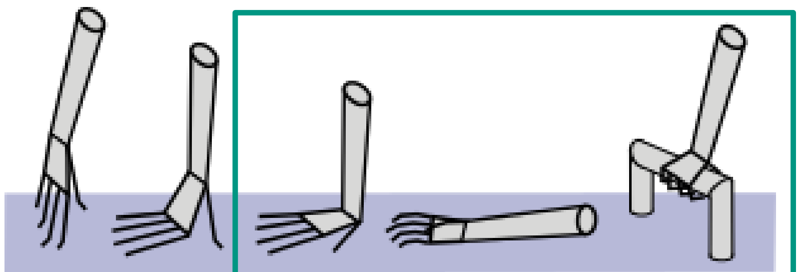
1 Foot 1 Knee

It depends on types of contacts considered!

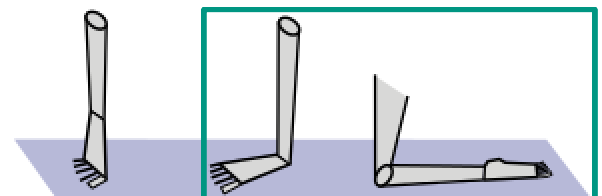
Type of contacts

- Possible contacts with extremities

Type of contacts with arms



Type of contacts with legs



- Combinatory between number of contacts and type of contacts considered

$$f(CL, CA) = \sum_{NL=1}^{2} \binom{CL + NL + 1}{NL} \cdot \sum_{NA=1}^{2} \binom{CA + NA + 1}{NA}$$

CA = # type of arm contacts

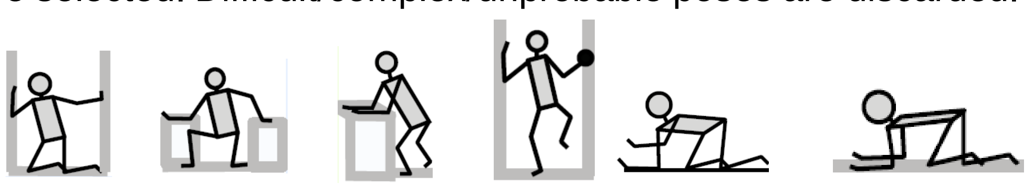
CL = # type of leg contacts

$$f(3,5) = 189$$

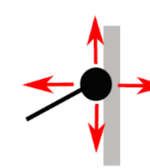
$$\boxed{f(2,3) = 50}$$

A total of 36 poses are selected. Difficult/complex/unprobable poses are discarded.

Examples of **discarded** poses

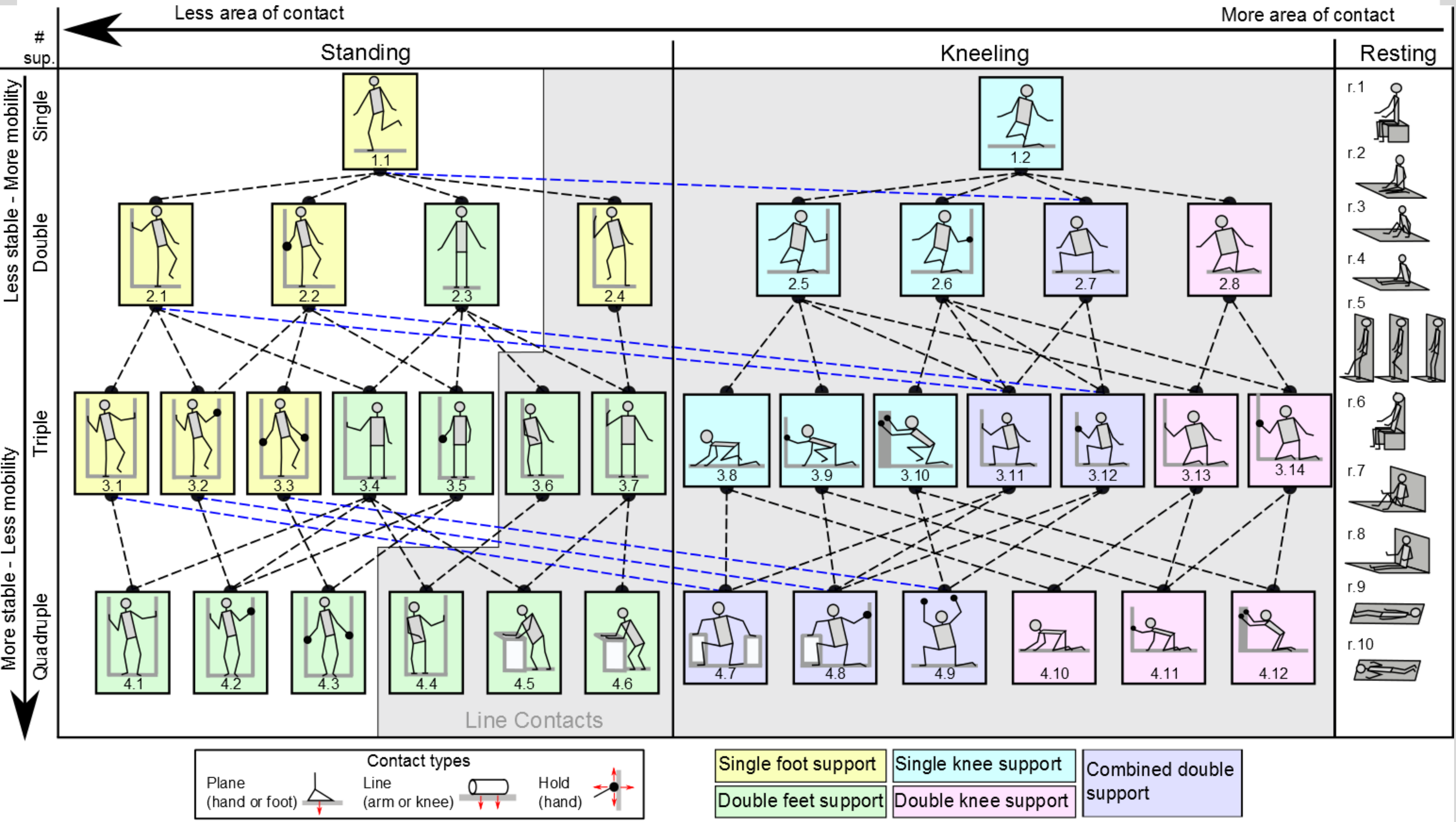


Hold is represented as a dot



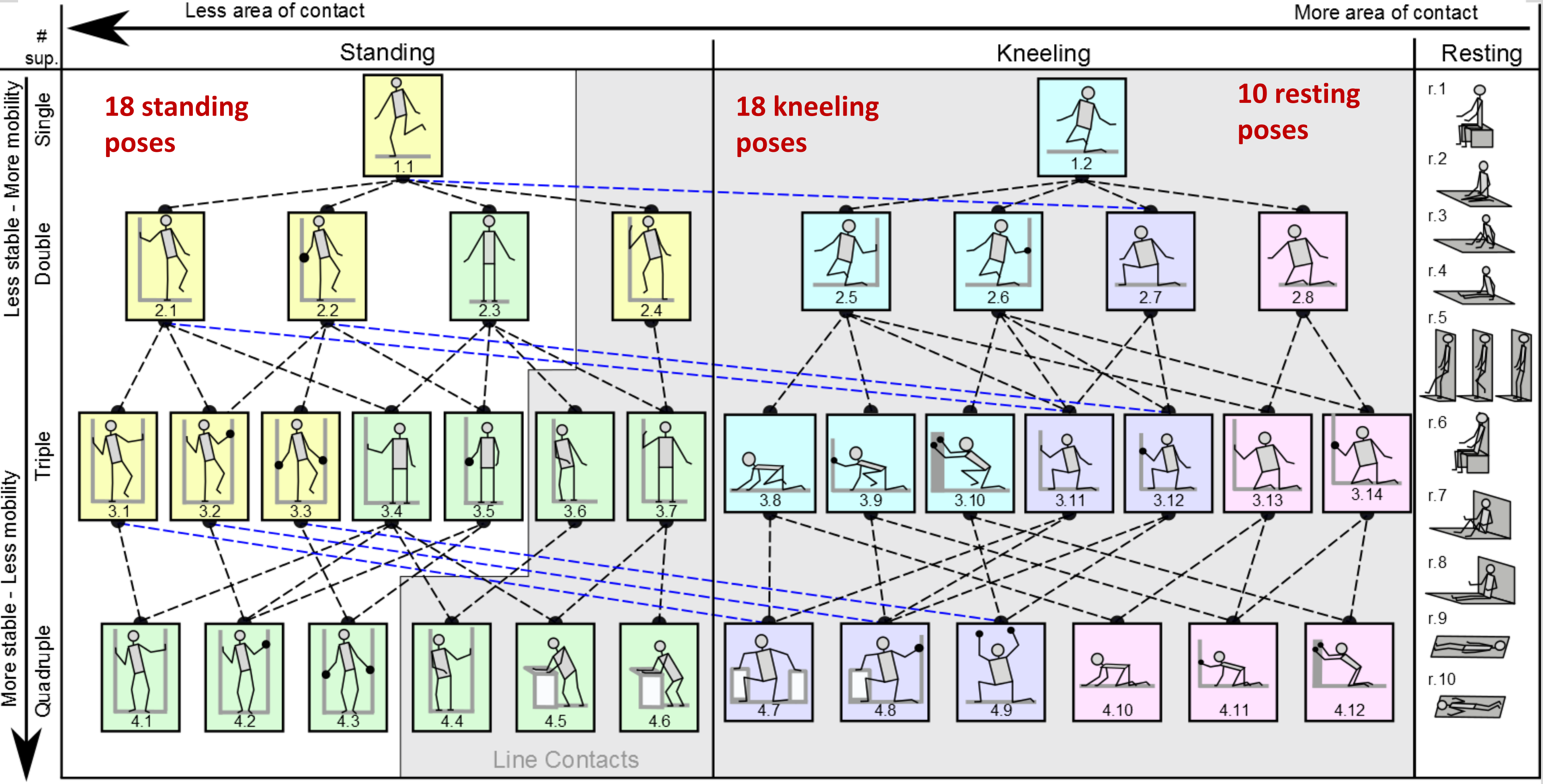
Taxonomy of whole-body poses

Karlsruhe Institute of Technology



Borras and Asfour, IROS 2015

Taxonomy of whole-body poses

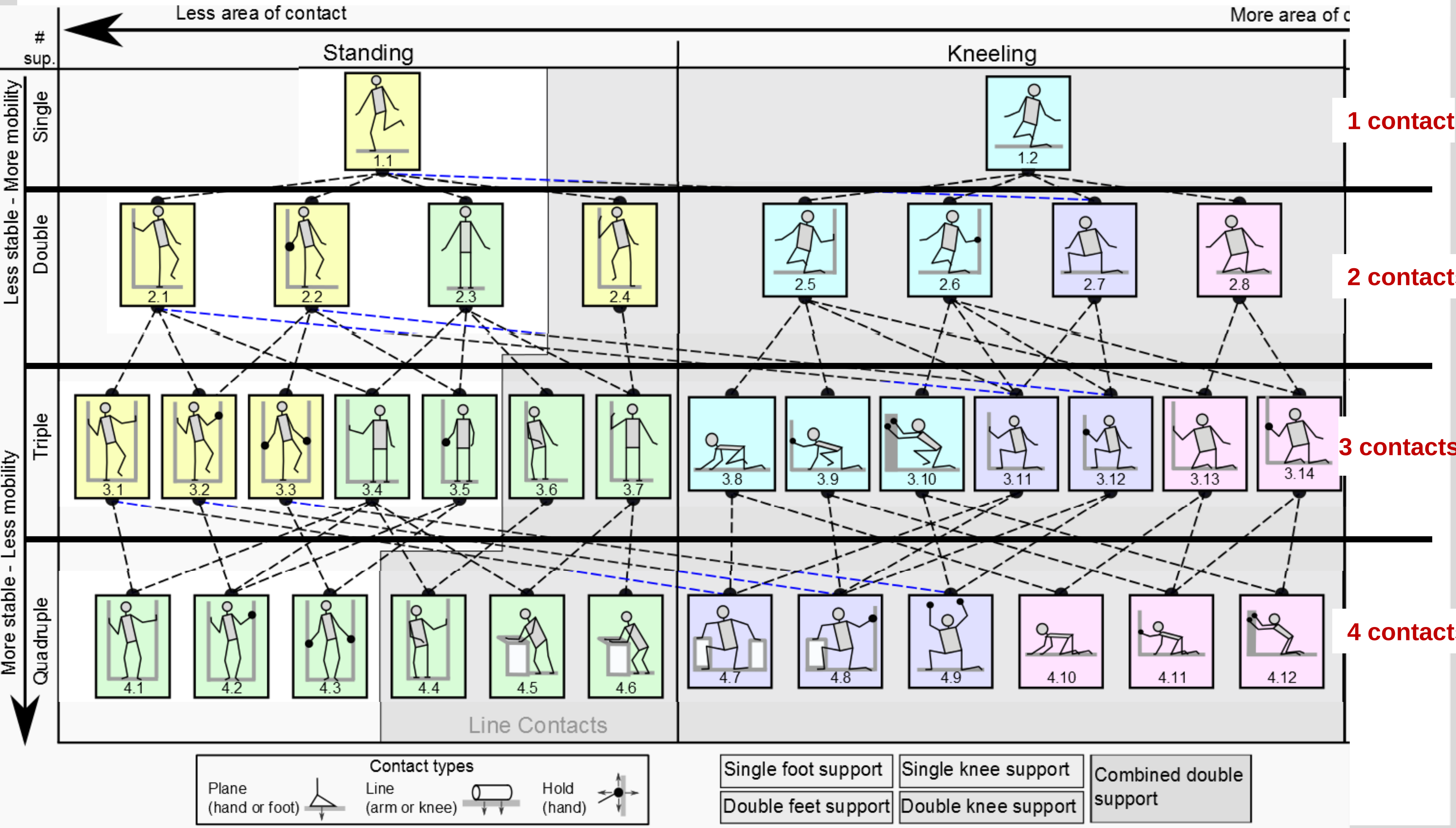


Total: 46 classes

Borras and Asfour, IROS 2015

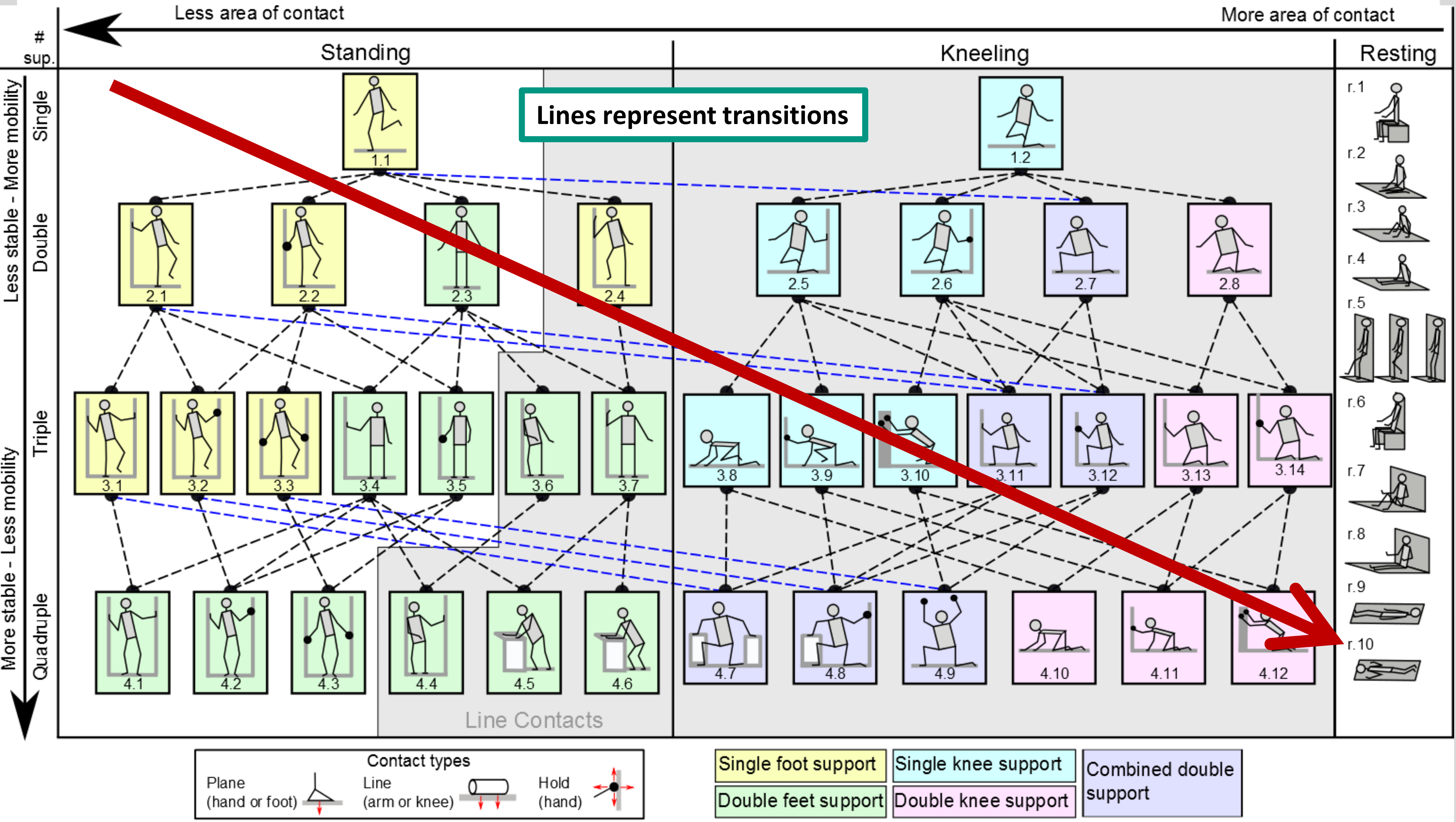
Taxonomy of whole-body poses

Karlsruhe Institute of Technology



Borras and Asfour, IROS 2015

Taxonomy of whole-body poses



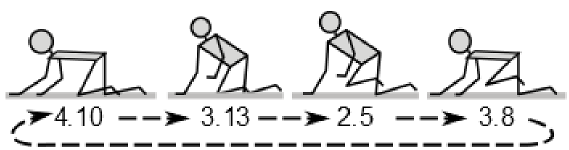
Classification of whole-body actions

- Type I: Actions to change the environment
  - One support pose is selected to perform the **manipulation**
  - Only rows 1 to 3 of taxonomy allow manipulation actions

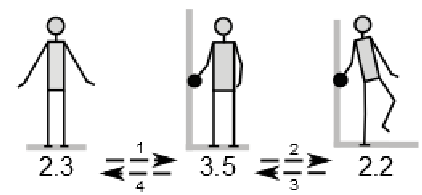
Ex. of pose selection for action "Hit an object"

- Type II: Actions to change the body
  - Succession of support poses to allow **locomotion** or **balancing**
  - All rows of taxonomy can be used

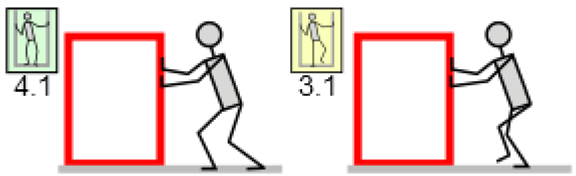
Crawling



Walk on stairs with handle

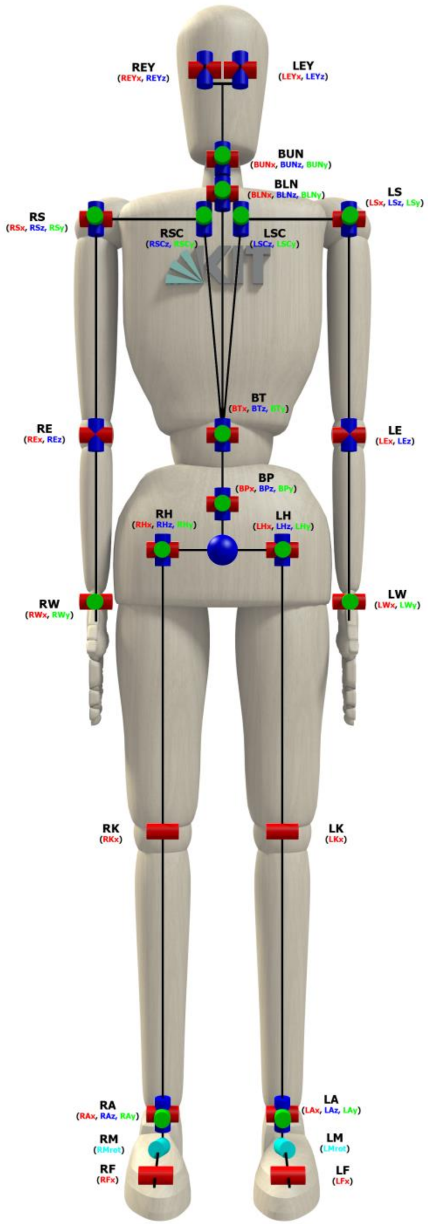


- Type III: Combination of I and II
  - Contacts are used to balance and to change the environment
  - Only rows 2 to 4 of taxonomy



Validation of the taxonomy

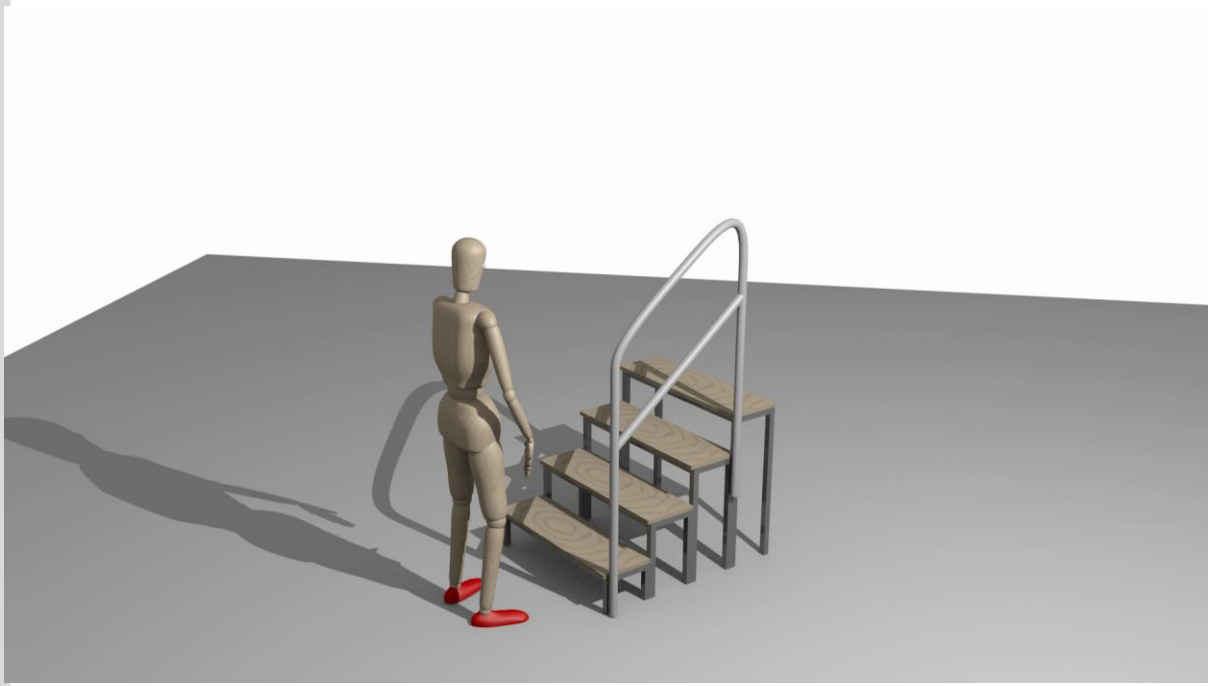
- Analyses of different human loco-manipulation tasks with supports
- Reference model of the human body (Master Motor Map: MMM) with 104 DoF
- Motion capture data mapped to reference model of the human body (MMM)
- Automatic segmentation to detect support poses and transitions
- Automatic generation of a taxonomy of the poses and their transitions in the motion database



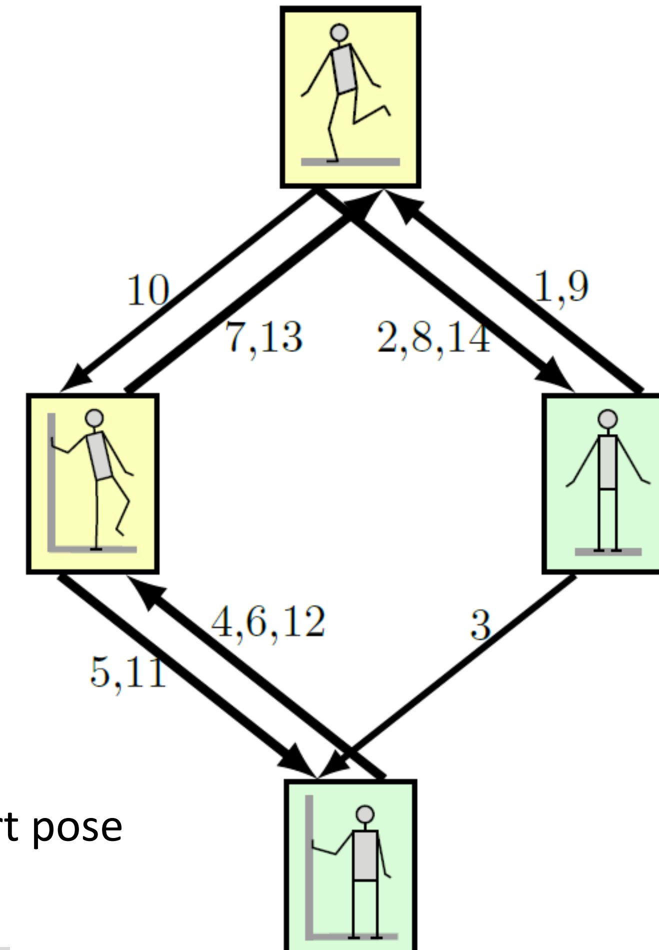
Analysis of pose transitions

Going upstairs with a handle

Detection of support contacts highlighted in red



Generated graph of transitions:

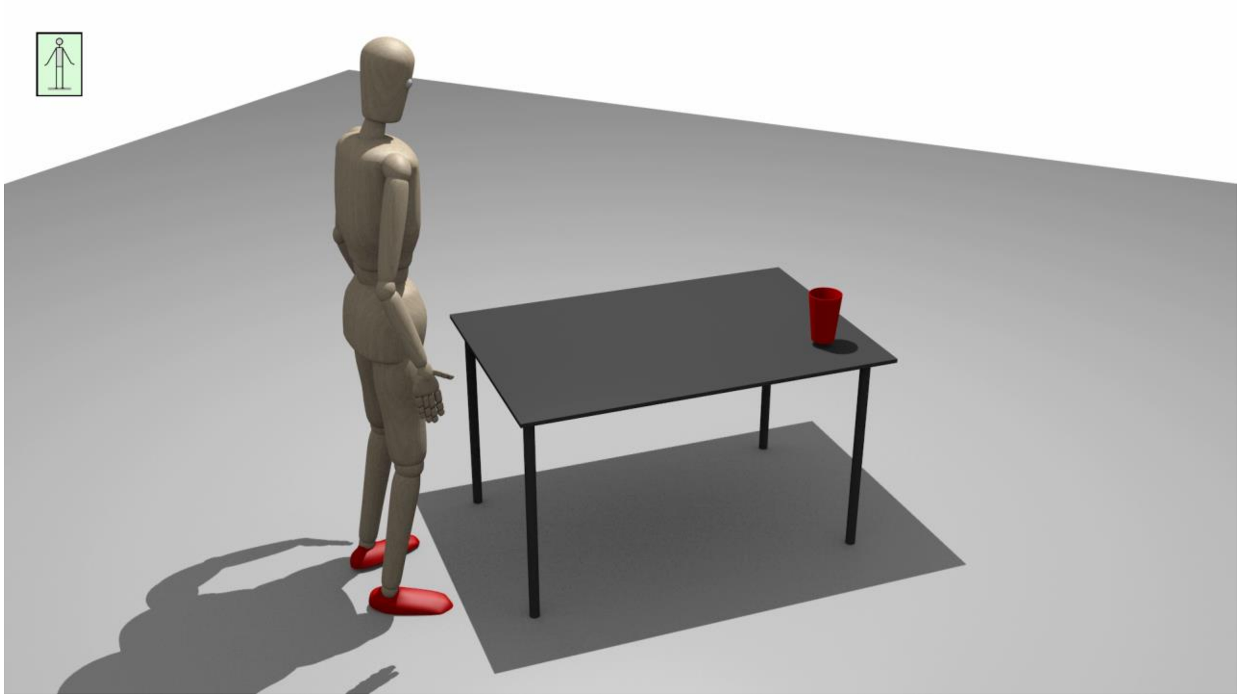


Subject swings left foot with a *right foot – right hand* support pose

Analysis of pose transitions

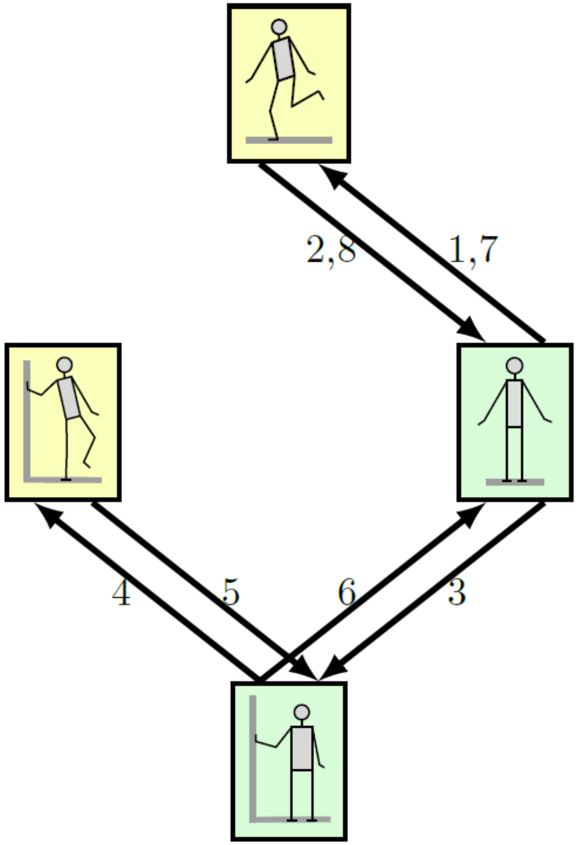
Lean on table to pick up a cup

Detection of support contacts highlighted in red



The manipulation takes place on a *one Hand – one Foot* support pose

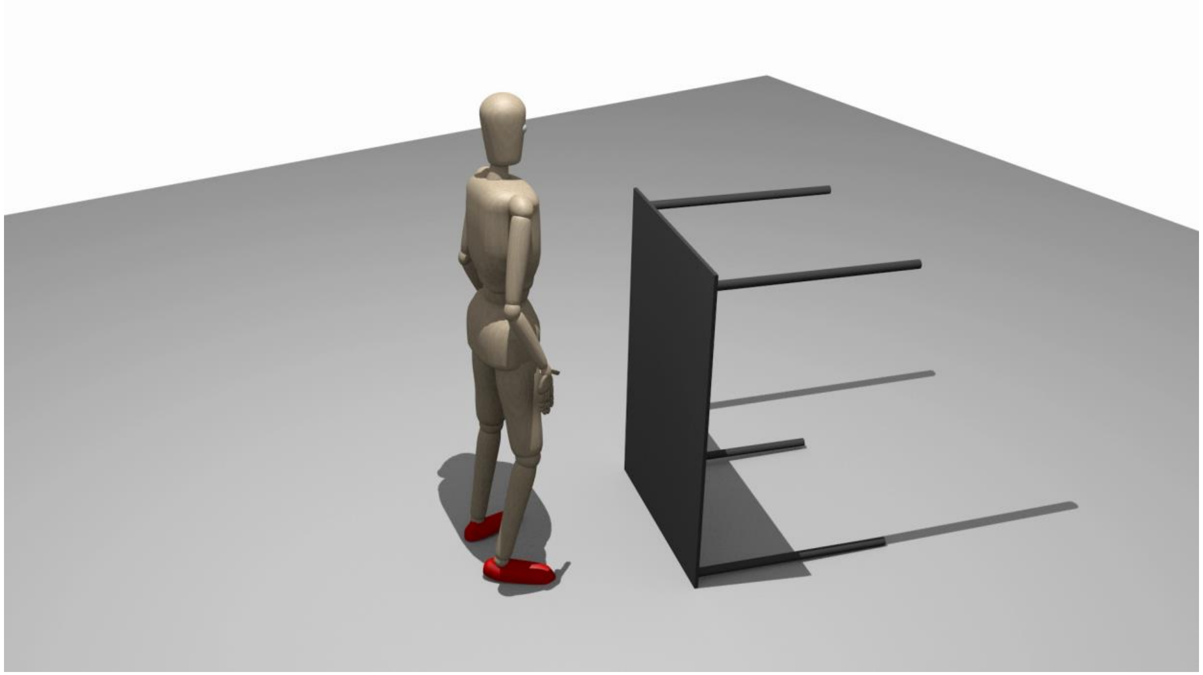
Generated graph of transitions:



Analysis of pose transitions

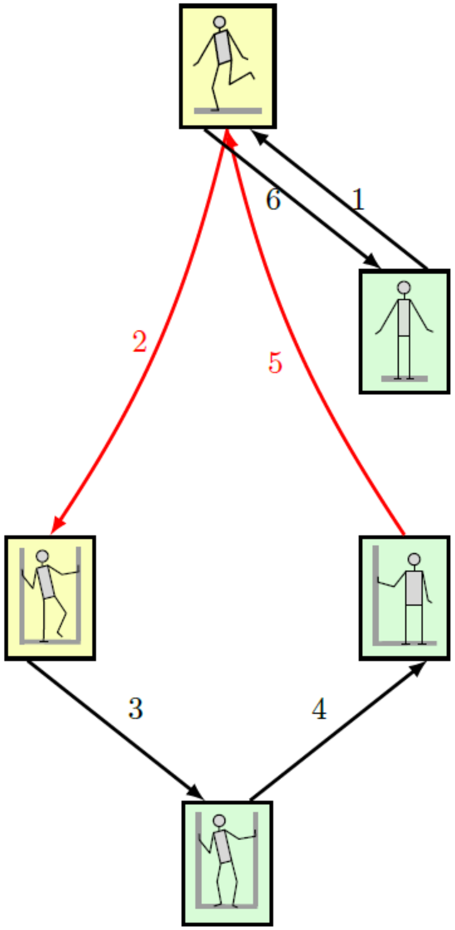
Push recovery from a push from behind

Detection of support contacts highlighted in red

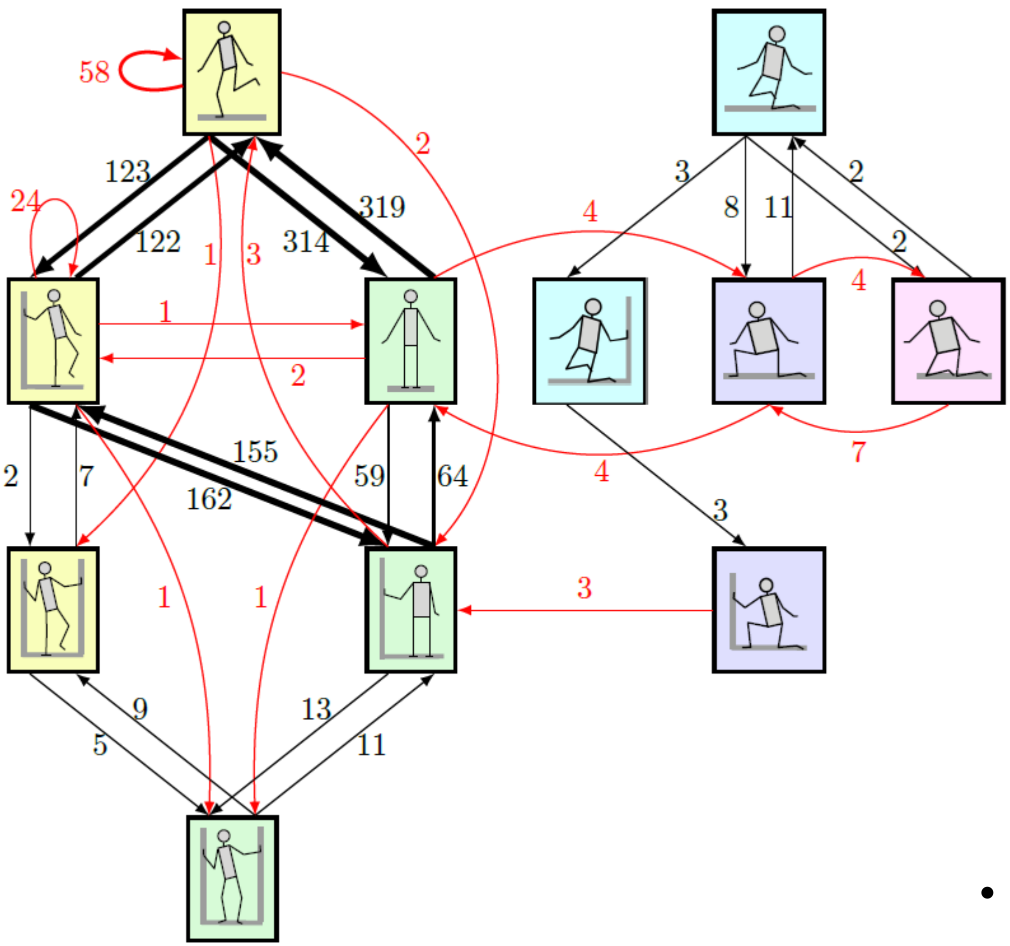


Transitions with 2 changes of contacts.

Generated graph of transitions:

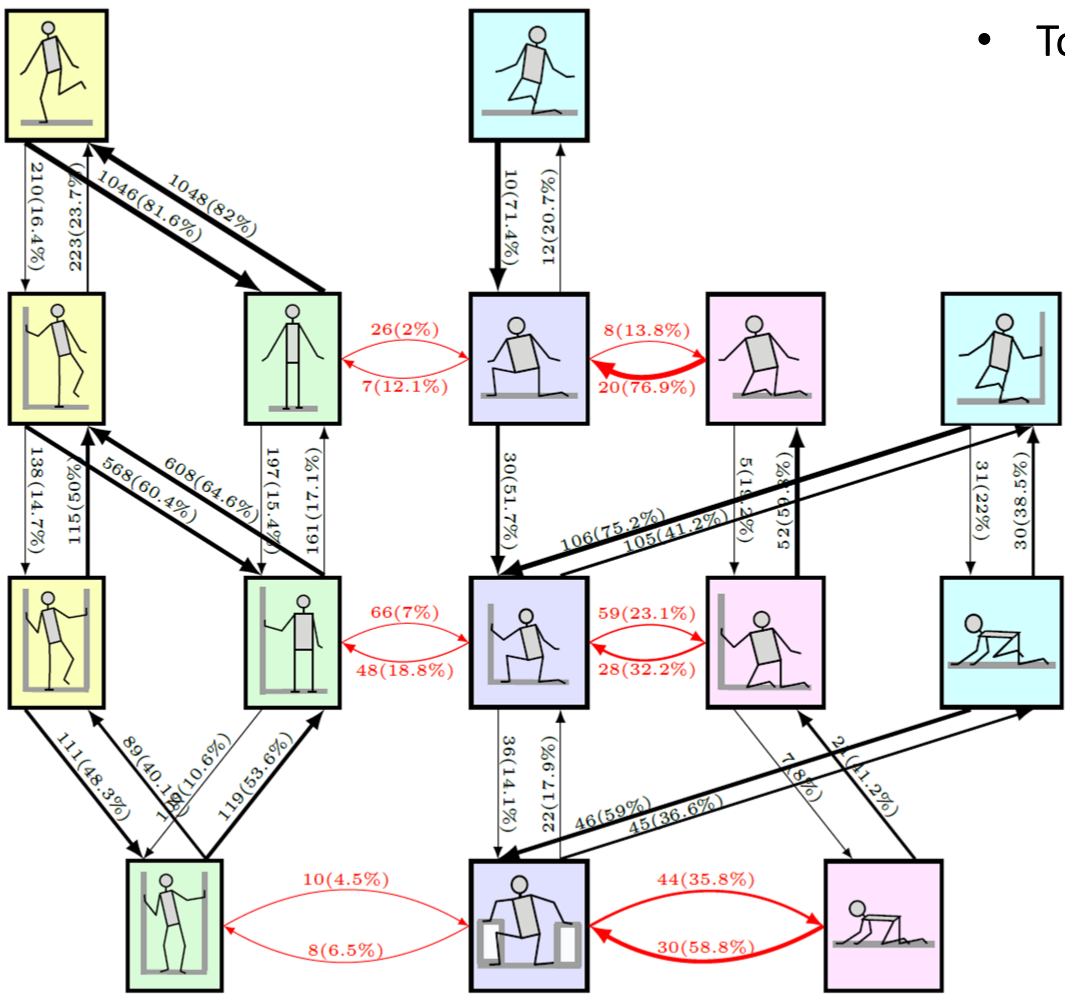


Validation of the taxonomy



- Total of **121** motions processed
  - **Locomotion**
    - Upstairs/downstairs with handle
    - Walk with handle
    - Walk avoiding obstacles using hand supports
  - **Loco-manipulation**
    - Lean to reach/place/wipe
    - Bimanual pick and place of big objects
  - **Balancing**
    - push recovery
    - recovery due to lost balance
  - **Kneeling motions**
- 4,5% of poses missed (all double foot supports (the looping edges))

Validation of the taxonomy



- Total of **388** motions processed
  - **Locomotion**
    - Upstairs/downstairs with handrail
    - Walk with handrail
    - Walk using table for supports
    - Kneeling up and down
    - Crawling

Postural Synergies and Eigengrasps

Postural Synergies

- **Literature**
  - Marco Santello, Martha Flanders, John F. Soechting. ***Postural Hand Synergies for Tool Use***, The Journal of Neuroscience, 18(23): 10105-10115 (1998)
  - Antonio Bicchi, Marco Gabiccini, Marco Santello. ***Modelling natural and artificial hands with synergies***, Philosophical Transactions of the Royal Society B, 366: 3153-3161 (2011)

Red: relevant for the exam

Introduction

- Questions:
  - How do humans grasp?
  - Do they control all the hand's DoF individually?
- Answer from human grasping experiments:
  - "Experimental evidence indicates that the simultaneous motion and force of the fingers are characterized by coordination and covariation patterns that reduce the number of independent degrees of freedom to be controlled.“ (Bicchi et al., 2011)
- In other words:
  - Not all finger joints are controlled independently when grasping an object.
  - Movements of the finger joints are strongly correlated.
  - Grasping movements are dominated by synergies in a (low-dimensional) posture space.
- What are postural synergies?
  - Postural synergies are the correlation of degrees of freedom in patterns of more frequent use.

Postural synergies - Experiment

- Human subjects were asked to perform grasp motions for various objects.

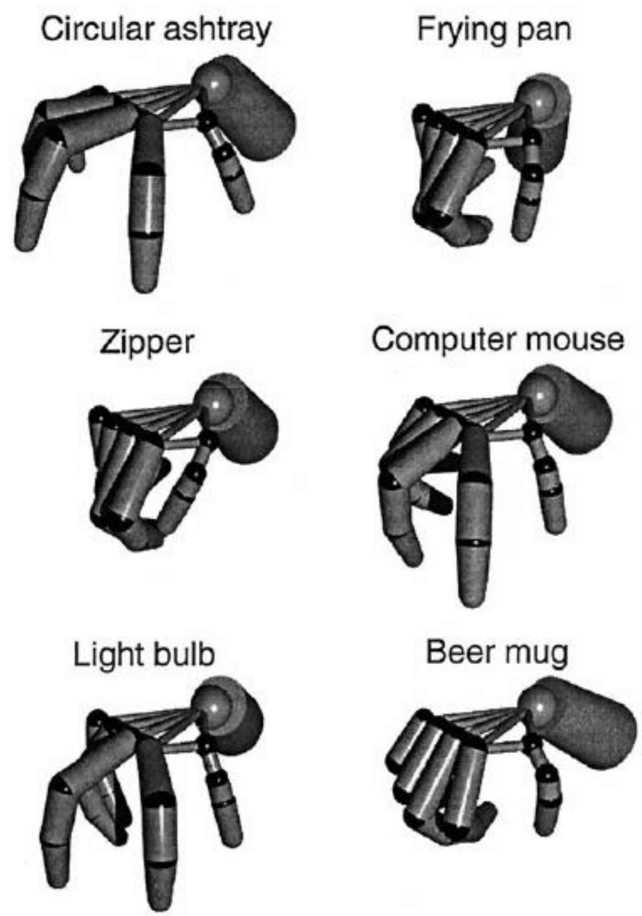
- No real objects were present, but the participants only imagined to grasp a large number of objects (n = 57) and moved the hand to a corresponding grasp configuration

Table 1. List of objects used in the task

1. Apple	30. Hammer
2. Banana	31. Ice cube
3. Baseball	32. Iron
4. Beer bottle	33. Jar lid
5. Beer mug	34. Kitchen knife
6. Brick	35. Knob of a lid
7. Bucket	36. Knob of a stove
8. Calculator	37. Light bulb
9. Chalk	38. Milk carton
10. Cherry	39. Needle
11. Chinese tea cup	40. Notebook
12. Cigarette	41. Pen
13. Circular ashtray	42. Playing card
14. Coffee mug	43. Rope
15. Comb	44. Scissors
16. Compact disc	45. Screwdriver
17. Computer mouse	46. Stapler
18. Dictionary	47. Sugar cone
19. Dinner plate	48. Teaspoon
20. Dog dish	49. Telephone handset
21. Door key	50. Tennis racket
22. Door knob	51. Toothbrush
23. Drawer handle	52. Toothpick
24. Egg	53. Turtle
25. Espresso cup	54. Umbrella
26. Fishing rod	55. Wafer
27. Frisbee	56. Wrench
28. Frying pan	57. Zipper
29. Hair dryer	

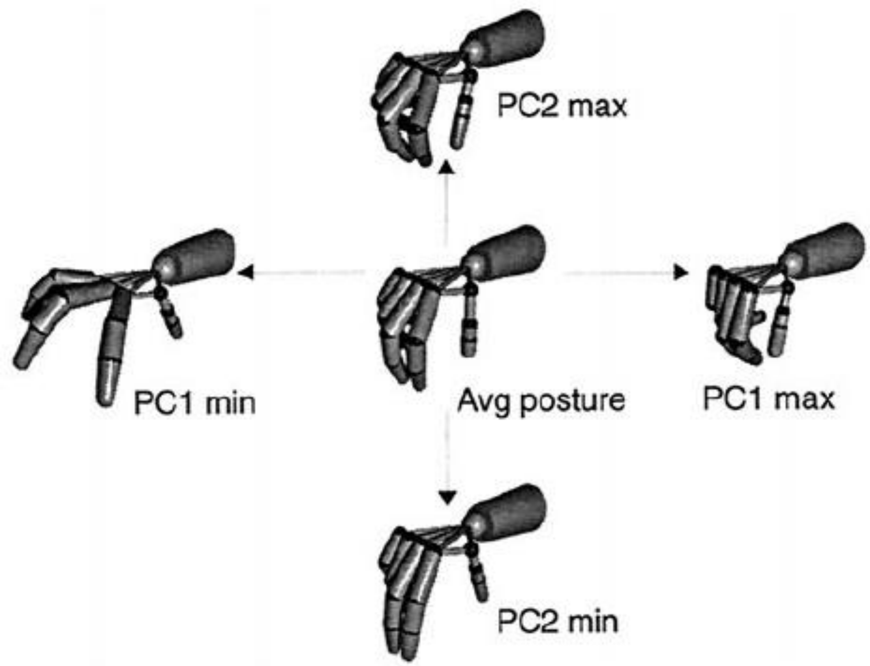
Postural synergies - Experiment

- The hand movement was observed and measured by 15 sensors embedded in a glove (CyberGlove)
- Measurement sample rate 12 msec
- Each hand posture describes a joint angle configuration of the human hand approximated by a 15 DoF hand model.



Postural synergies - Results

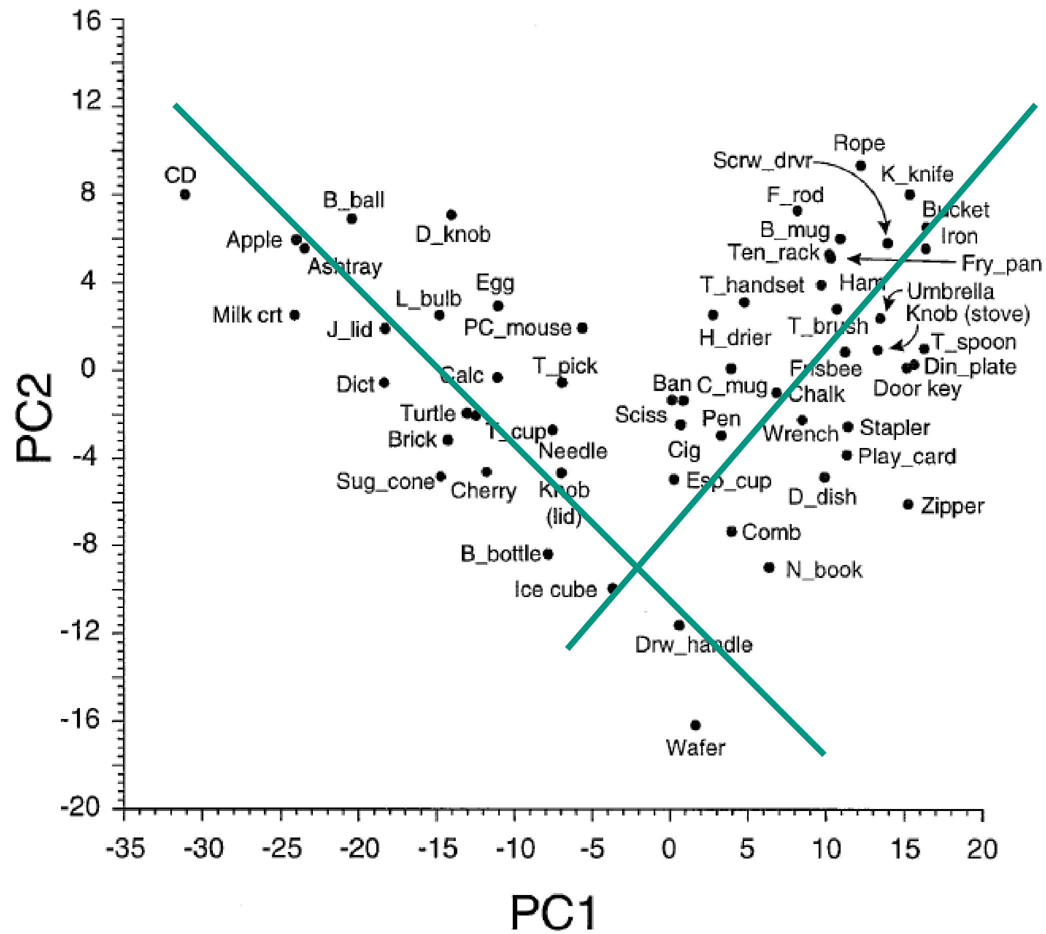
- Principal Component Analysis on the data:
  - During grasping, the hand moves in a low-dimensional subspace.
  - Considering only the first two principal components, 80% of the variance in the data can be represented.
  - Using the first three principal components, 97% of the variance can be represented.



- Postural synergies defined by the first two principal components (PC1 and PC2)
- The hand posture at the center of the PC axes is the average of 57 hand postures for one subject.
- Images rendered with the palm of the hand in the same orientation

Postural synergies - Results

- Distribution of hand postures in the plane of the first two principal components.
- The coefficients of the first two principal components are shown for each of the 57 objects for one subject.
- Note the lack of clustering and the distribution of the coefficients along two main axes.



Postural synergies - Results

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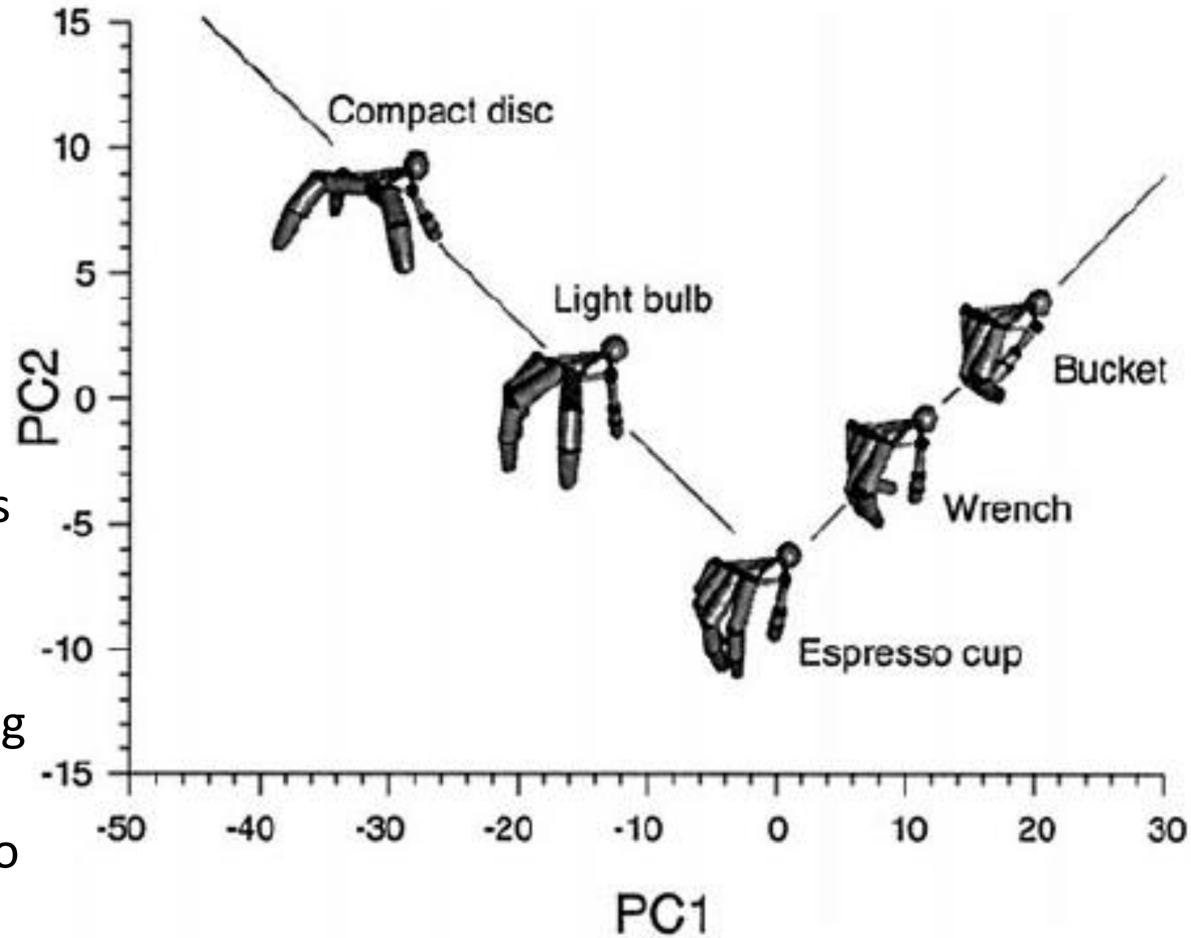
Interpolation between various grasp postures



Postural Synergies – subject variance of the PCs

Subjects	PC_1	PC_2		PC_3	PC_4
FC	52.9	24.7	77.6	8.4	4.8
GB	49.5	37.6	87.1	4.8	4.6
MF	74.8	13.0	87.8	5.4	2.9
MS	79.3	10.0	89.3	5.0	2.2
UH	62.9	17.2	80.1	8.6	5.9

- The first three PCs account for ~ 90% of the variance
- The first two PCs account for ~ 84% of the variance
- This suggests a significant reduction in the number of degrees of freedom (DOF) from 15 to 2 or 3

Postural Synergies – How many effective DOF are there?

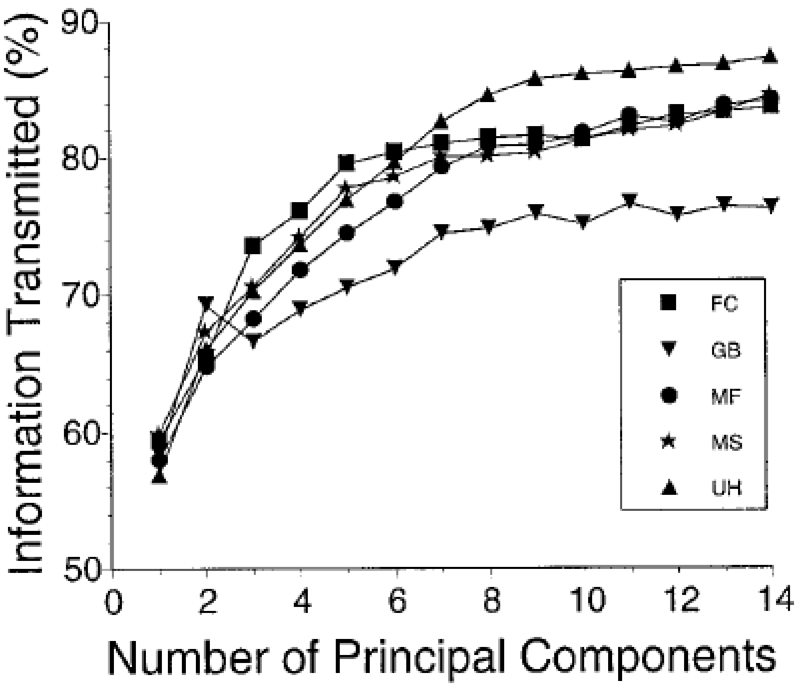
- The study shows also that there were also many instances in which pairs of joint angles were only poorly correlated, suggesting that there are more than two effective degrees of freedom for the control of hand posture and that several higher-order PCs would also be needed to represent this rather limited co-variation in joint angles

- There are two alternative solutions to this paradoxical result:
  - higher-order PCs are needed but represent noise (random variability) in the system
  - the higher-order PCs do in fact contribute to discriminating among hand shapes for different objects → additional DoF controlled by the CNS

- Additional analysis needed!

Postural Synergies – Role of higher-oder PCs

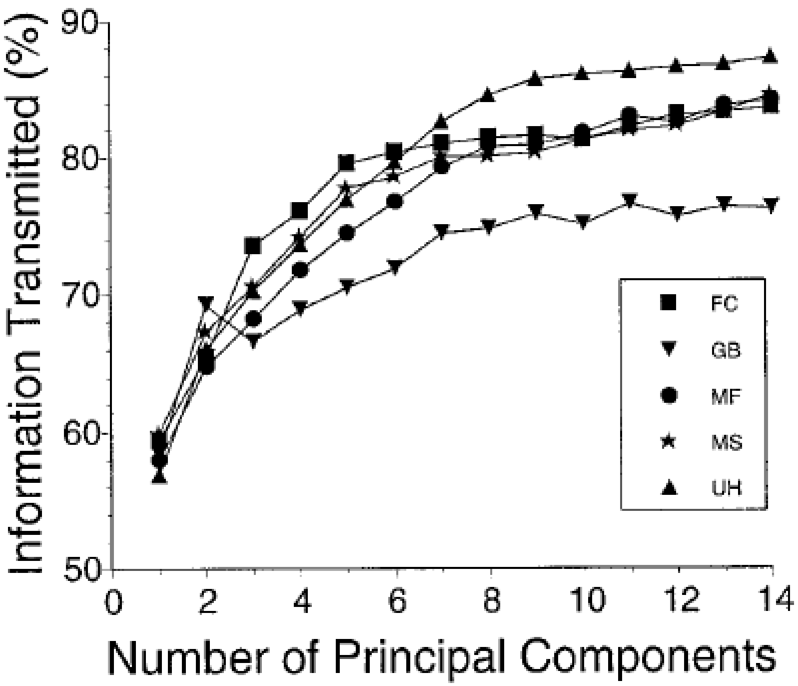
- Reconstruction of the hand posture using an increasing number of PCs (PC1, PC2, … PC14); PC15 was nearly zero
- Determine how much the representative information increased as the number of PCs increased
  - If the higher-order PCs represent noise, the information about the object should not increase (may actually decrease) when higher-order PCs are used to define the hand posture
  - Conversely, if the higher-order PCs do contribute to discriminating among hand shapes, the information transmitted should increase as more PCs are included.



Postural Synergies – Role of higher-oder PCs

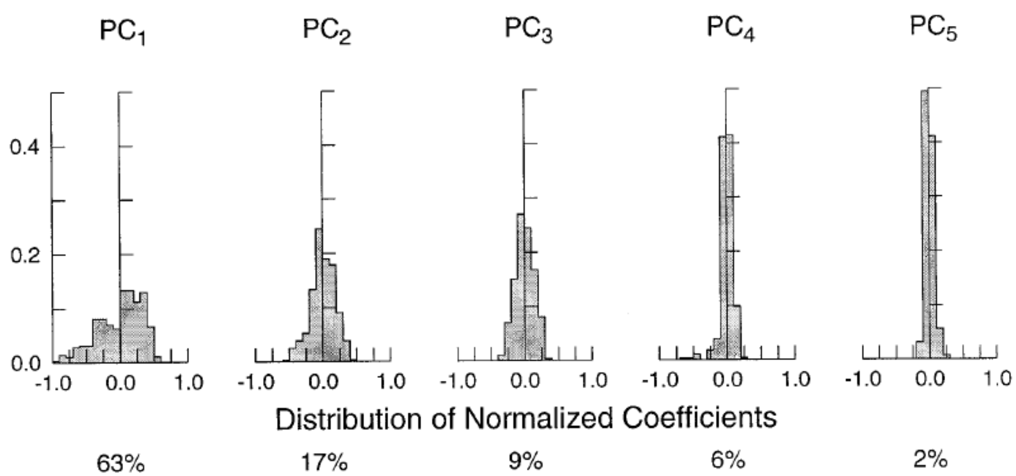
- The amount of information continued to increase monotonically up to at least the 5th or the 6th PC, even though these higher-order PCs contributed little to the variance

- Clearly, more than two degrees of freedom are used to mold the hand into the shape appropriate to grasp a particular object, and the higher-order PCs do not simply represent random variability (noise)

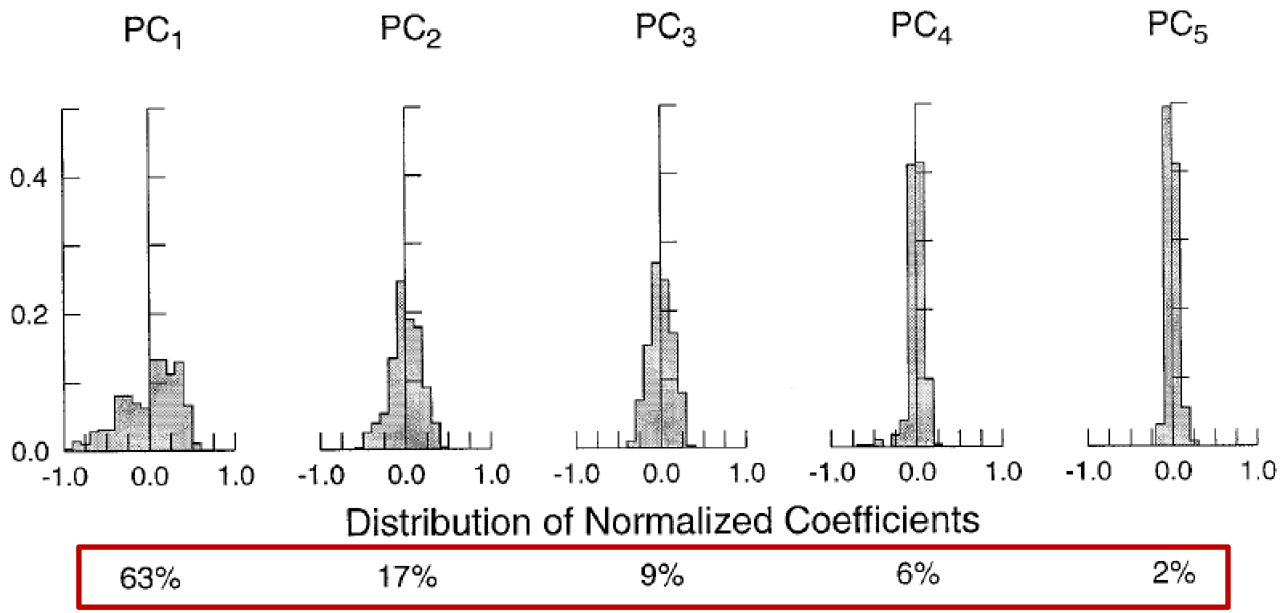


Postural Synergies – Role of higher-oder PCs

- Given that higher-order PCs do not simply represent noise, it is possible that the hand postures associated with a few of the objects might be best represented by higher PCs, i.e., that the amplitude of the higher-order PCs might be substantial for one or a few objects
  - Thus, the overall variance attributed to one PC might be small, but its contribution to a few postures might be large.
  - If this were the case, the distribution of the PCs for the 57 objects would be multimodal and/or have a broad range. But this is not the case (see Figure)



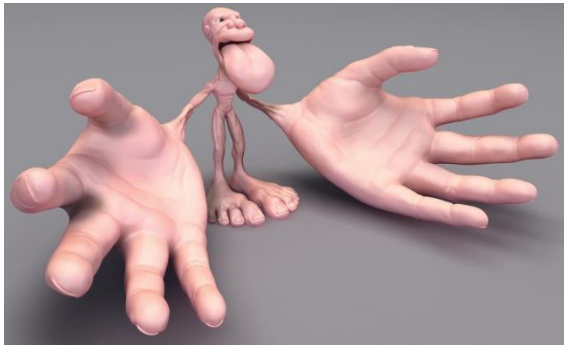
Postural Synergies – Role of higher-oder PCs



- Distribution of normalized amplitudes of the first five principal components. The amplitudes of the first five PCs have been normalized to the maximum (or minimum) value of the first PC. The data shown are for one subject (U.H.). Note that the amplitudes of the 3rd through the 5th PCs are uniformly small, even though they contribute substantially to the information transmitted

Discussion

- This observation suggests the following interpretation.
  - The control of hand shape is effected at two levels. One coarse control of hand shape with a few synergies, and a finer level that may be affecting all the joints.
  - Because the higher-order principal components were very small and were not consistent from subject to subject, the study was not able to characterize this “finer level of control” more precisely.
  - The higher-order PCs had coefficients that were distributed among all of the joint angles, suggesting that this finer control is also distributed.
  - This hypothesis is consistent with the observation that a disproportionate amount of sensorimotor cortical area is devoted to the hand. It is also consistent with previous demonstrations of a tendency for coordinated motion of the fingers.



Conclusions of this work

- No evidence for a clustering of the static postures for the various objects was found
- Not straightforward relation object shape – hand shape
  - Similar object shapes were often associated with grips that were quite distinct (i.e., precision vs power grips).
- This supports previous classifications of grasps, based on which finger(s) and which part(s) of the finger(s) contacts and exerts force on the object
- Relationship between static hand posture (i.e., kinematics) -- control of contact force.
  - They are **not** independent, because the hand must be shaped properly so that the correct set of fingers makes contact with the object.
  - But there is no one-to-one relation between posture and force control
  - i.e., very different contact forces may be exerted with the hand in the same posture, depending on the object
- This is consistent with observations of neural activity in the hand area of primary motor cortex:
  - Monkeys controlling the grasp force of variously shaped objects showed that
  - The neural correlates of force and
  - The neural correlates of kinematics

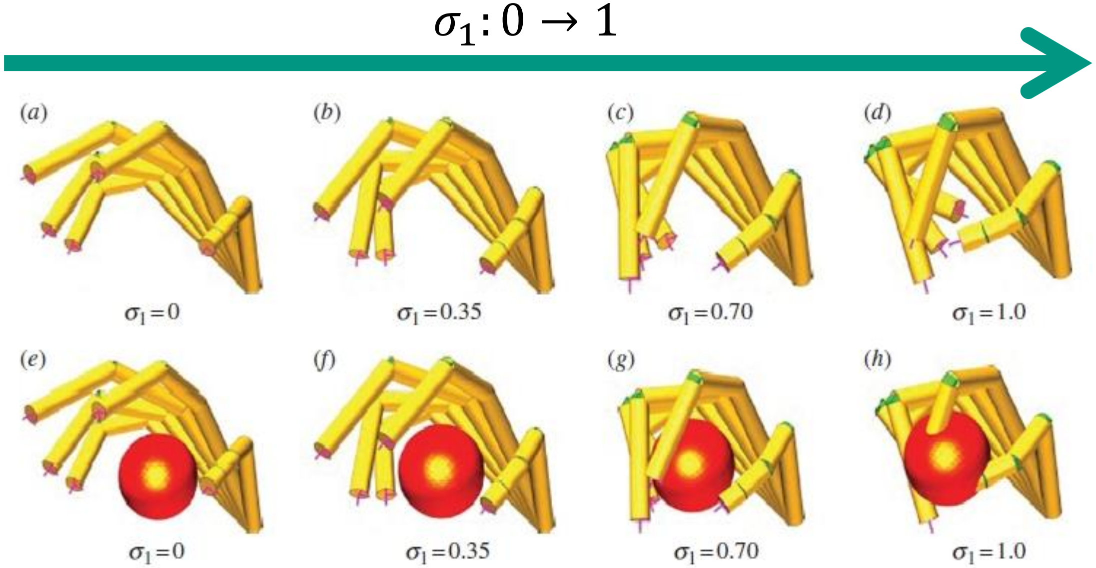
Are dissociatiated

Antonio Bicchi, Marco Gabiccini, Marco Santello. ***Modelling natural and artificial hands with synergies***, Philosophical Transactions of the Royal Society B, 366: 3153-3161 (2011)

Problems with the synergistic model so far

- Synergies can’t be modeled as rigid manifolds.
- Example: Using the first synergy, when the hand closes around the object ($\sigma_1 : 0 \rightarrow 1$), if touches first with index and thumb at $\sigma_1 = 0.75$ and after that fingers penetrate the object
  - Contact forces of the object not considered
  - No compliance in the hand
- Consequently, a new model is necessary.

$\sigma_1 : 0 \rightarrow 1$



The Soft Synergy Model (1)

- Human hand (as an example):
  - Compliance in the human hand is introduced by the musculotendinous system.
  - Redundancy in the apparatus, together with its nonlinear elastic characteristic is used for changing the compliance of the agonist-antagonist pairs

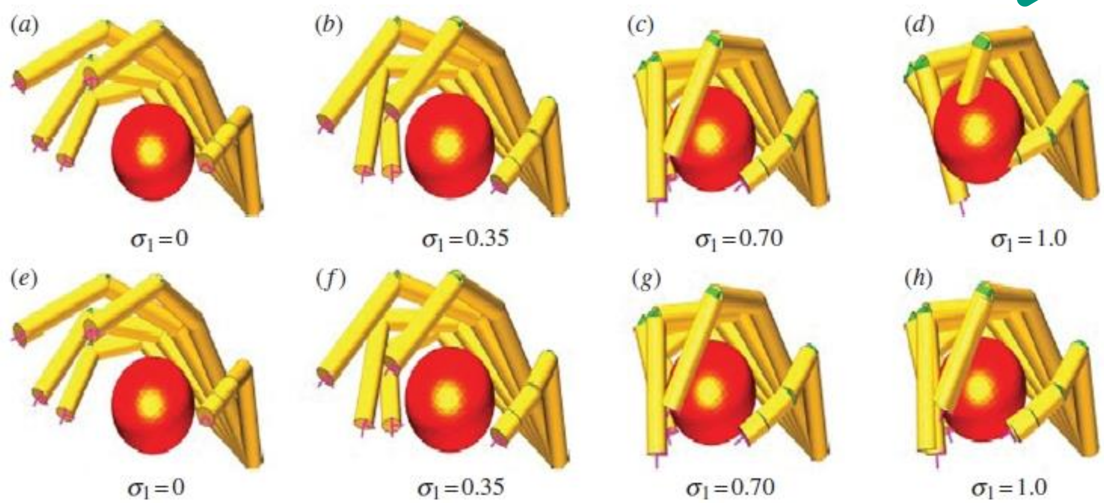
- Question: How can a model of elasticity be introduced into the synergy model?

- Answer: Use a combination of two force fields to control the physical hand.
  - One field is attracting the physical hand towards a virtual hand (which is shaped on the synergy manifold). The attraction forces are generated by the hand impedance.
  - The other field is repelling the hand from penetrating the object.

The Soft Synergy Model (2)

- The dynamical equilibrium between the two fields is found depending on the stiffness (more generally: mechanical impedance) of the hand actuation and control system.

$\sigma_1 : 0 \rightarrow 1$



  - Reference hand moves on the synergy manifold (a-d) and represent an attractor for the real hand.
  - Real hand is repelled by contact forces with the object (e-h).

Synergies in Force Distribution

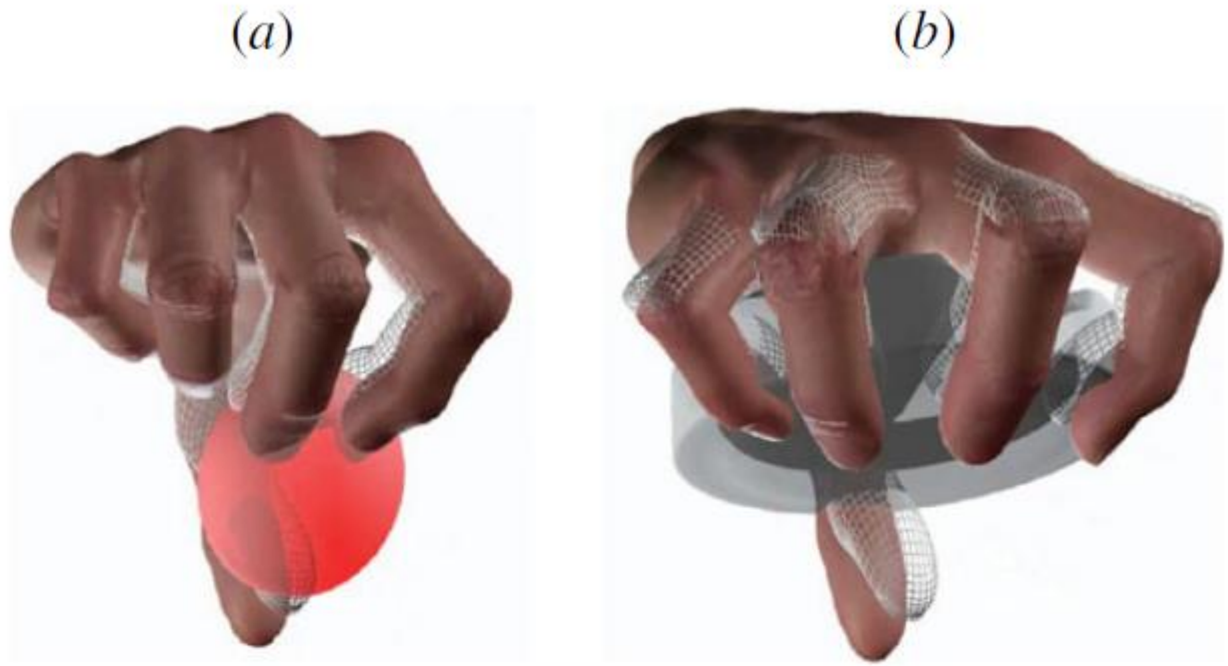
- Questions:
  - Is the soft synergy model relevant to grasping?
  - Can the first few synergies (which where observed to generate a large part of pre-grasp postures) also explain the distribution patterns for grasp forces?

- Answer:
  - Yes. Application of the soft synergy model also allows making predictions on force distribution in manipulation (see experiment)

Experiment

- Associate each postural synergy through a numerical model of hand and object compliance to a contact force pattern.
- Combine the resulting force synergies linearly with weights in order to minimize a grasp cost index.
- The grasp index reflects the capability of the grasp to resist external forces while avoiding slippage of the object in the hand (force-closure) and also weighs factors such as required actuator torques.
- Examples:
  - Precision grasp of a cherry-like object
  - Power grasp of an ashtray

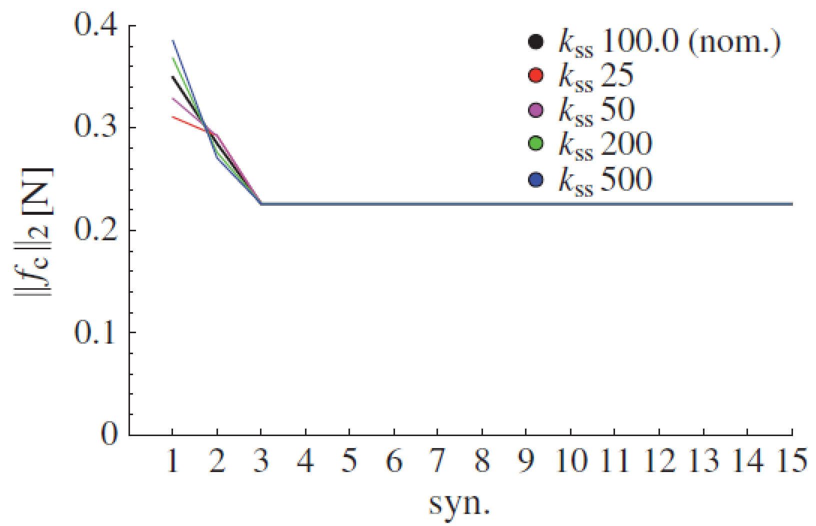
Application of the soft synergy model to grasping

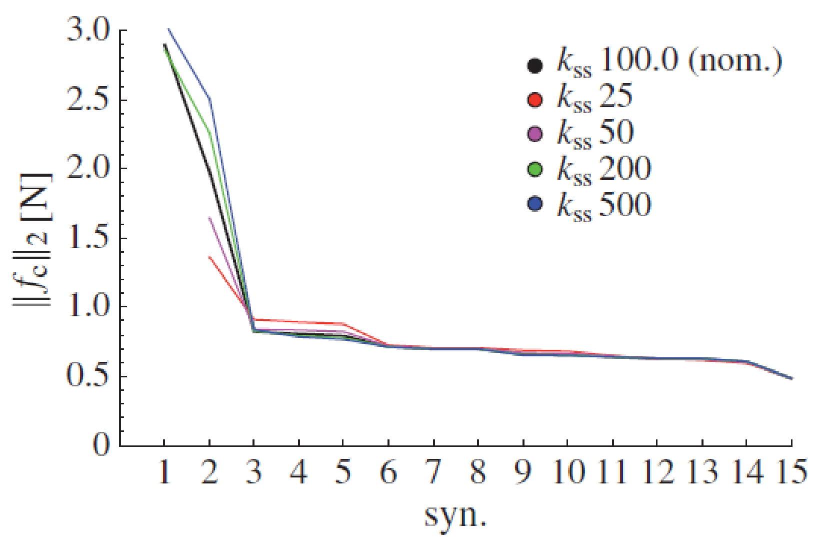


In wireframe is the reference hand, moving according to the constraint manifold corresponding to the first three synergies.

Results

- The force-closure property of grasps strongly depends on which synergies are used to control the hand.
- Grasp cost index variations with increasing number of synergies involved, for different hand compliance values
- No improvement is observed beyond the first three synergies in the precision grasp case (top figure), while continuous but small improvements are obtained in the whole-hand grasp case (bottom figure).





Long-term goals of research in hand synergies

- Long-term goal:
  - Define a set of synergies, ordered by increasing complexity
  - Define a correspondence between
    - A task (in terms of a number of different grasps, explorative actions and manipulations),
    - The least number of synergies to make the task feasible.

- A hand for basic grasps only could use the first two or three synergies in the basis.

- A manipulative hand with fine motion control of single joints (such as a piano player's hand) may require coordination of many more synergies.

Eigengrasps:
Grasp planning based on postural hand synergies

Eigengrasps – Introduction

- The grasp planning problem in robotics:
  - Find a hand pose and configuration (joint angle vector) relative to a known object such that the contact locations between hand and object prevent object motion relative to the hand, i.e. a stable grasp is achieved.
- This can be treated as an optimization problem:
  - Vary hand pose and configuration until distances between desired hand contact points and object surface are zero and a mechanical stability criterion is satisfied.
- However, the hand has:
  - 6 DoF pose
  - 21 DoF configuration/posture (in case of the human hand)
- Solving a non-linear optimization problem in 27-dimensional space may take very long.

Eigengrasps – Idea

- Idea:
  - Do not use the complete 21 DoF hand configuration for the optimization process.
  - Instead, use only the first two hand synergies obtained from human grasping observations.
  - Thus, the 27-dimensional optimization problem is reduced to a 8-dimensional optimization problem.
  - Theoretical justification: Most of the possible useful grasps should be found in the vicinity of a small set of points in configuration space.
- In 2007, Ciocarlie presented a grasp planning algorithm based on this idea and coined the term "eigengrasps“ for the principal components of the human grasp configuration data.

Matei Ciocarlie, Corey Goldfeder, Peter Allen. *Dimensionality reduction for hand-independent dexterous robotic grasping*, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), (2007)

Eigengrasps – Formalism

- Let d be the total number of DoF of the hand and θ_i the i-th DoF, then a hand configuration $\boldsymbol{p}$ can be defined as

$$\boldsymbol{p} = [\theta_1, \theta_2, \dots, \theta_d] \in \mathbb{R}^d.$$

- Each eigengrasp e_i is a d-dimensional vector and can also be thought of as direction of motion in joint space:

$$\boldsymbol{e_i} = [e_{i,1}, e_{i,2}, \dots, e_{i,d}] \in \mathbb{R}^d$$

- The idea is now that the eigengrasps $\boldsymbol{e_i}$ form a low-dimensional basis for grasp configurations, and can be linearly combined to closely approximate most common grasping configurations.

Eigengrasps – Formalism (cont‘d)

- By choosing a basis comprising b eigengrasps, a hand configuration placed in the subspace defined by this basis can be expressed as a function of the amplitudes a_i along each eigengrasp direction

$$\boldsymbol{p} = \sum_{i=1}^{b} a_i \boldsymbol{e_i}$$

- A hand configuration is therefore completely defined by the amplitudes vector

$$\boldsymbol{a} = [a_1, \dots, a_b] \in \mathbb{R}^b.$$

Eigengrasps

- Similar to the human hand, eigengrasps for robotic hands can be defined by combining several DoF of the respective hand:

Model	DOFs	Eigengrasp 1			Eigengrasp 2		
		Description	min	max	Description	min	max
Gripper	4	Prox. joints flexion	 →		Dist. joints flexion	 →	
Barrett	4	Spread angle opening	 →		Finger flexion	 →	
DLR	12	Prox. joints flexion Finger abduction	 →		Dist. joints flexion Thumb flexion	 →	
Robonaut	14	Thumb flexion MCP flexion Index abduction	 →		Thumb flexion MCP extension PIP flexion	 →	
Human	20	Thumb rotation Thumb flexion MCP flexion Index abduction	 →		Thumb flexion MCP extension PIP flexion	 →	

Eigengrasps – optimization problem

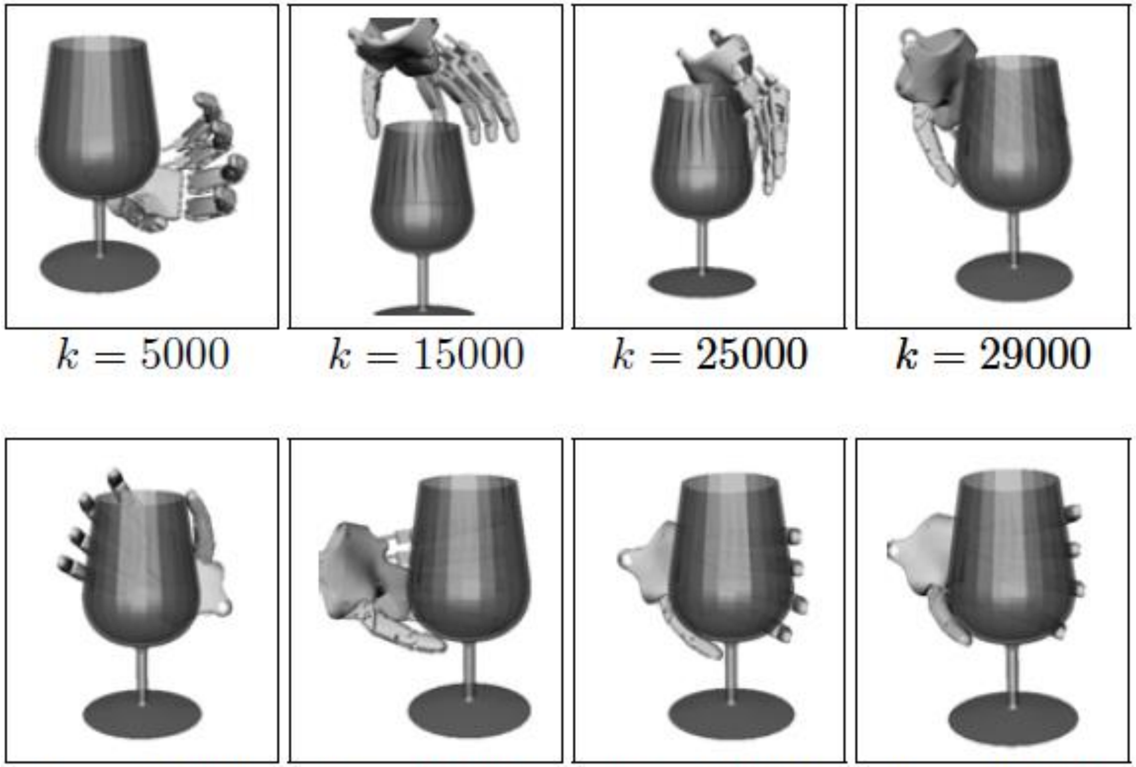
- In order to find stable grasps, one minimizes the energy function

$$E = f(\boldsymbol{a}, \boldsymbol{w})$$

- Equation symbols:
  - $\boldsymbol{a} \in \mathbb{R}^2$ is the vector of eigengrasp amplitudes
  - $\boldsymbol{w} \in \mathbb{R}^6$ is the vector describing the wrist pose
  - $f(.,.)$ is a function consisting of several components:
    - The sum of distances between the desired contact points on the hand and the object surface
    - The sum of angular differences between the orientation of the surface normals at the contact locations and the closest point on the object
    - A modified grasp quality measure based on the grasp wrench space
    - See (publicly available) source code of the *GraspIt!* simulator for further details: http://www.cs.columbia.edu/~cmatei/graspit/

Optimization process

- Use simulated annealing as an optimization algorithm
- Example: Best state found after *k* iterations

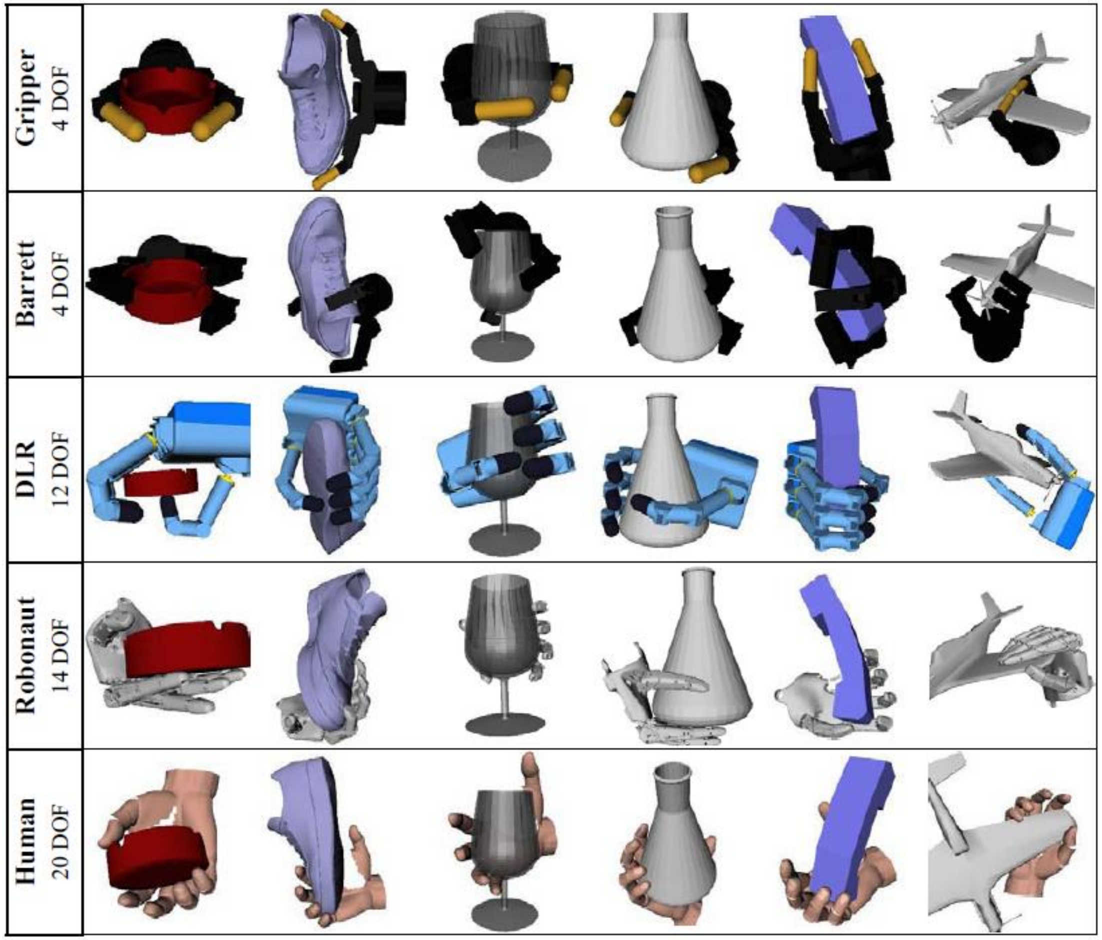


$k = 5000$ $k = 15000$ $k = 25000$ $k = 29000$

$k = 30000$ $k = 40000$ $k = 60000$ $k = 10000$

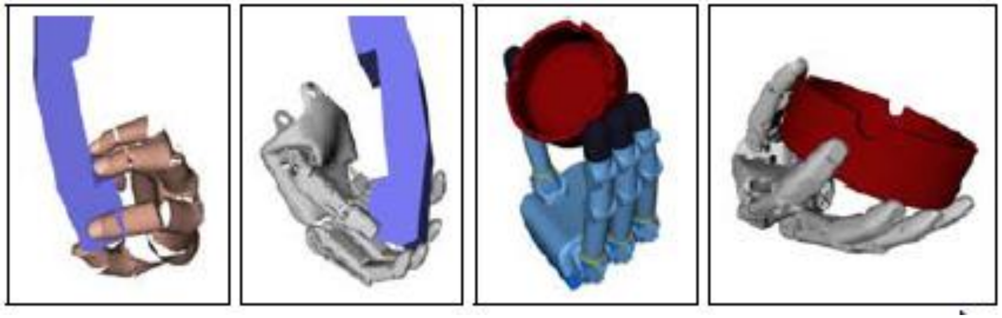
Eigengrasps

- Hand poses and configurations found by the optimization process for several hands and test objects



Eigengrasp planning – some further thoughts

- Optimization in the eigengrasp space with only two principal components does not necessarily lead to hand configurations where all (most) finger segments are in contact with the object‘s surface.
  - This is in line with the finding that the higher synergies are not simply noise but do in fact represent details of the object‘s shape.
  - Solution: After a fixed amount of iterations (or a certain period of time), stop the optimization process and close the finger joints until contact to the object prevents further motion.
- The algorithm does not work well with non-convex objects.
- The algorithm can be modified towards finding precision grasps by considering only desired contact points at the fingertips (see picture).



Implementation of synergies in robotics

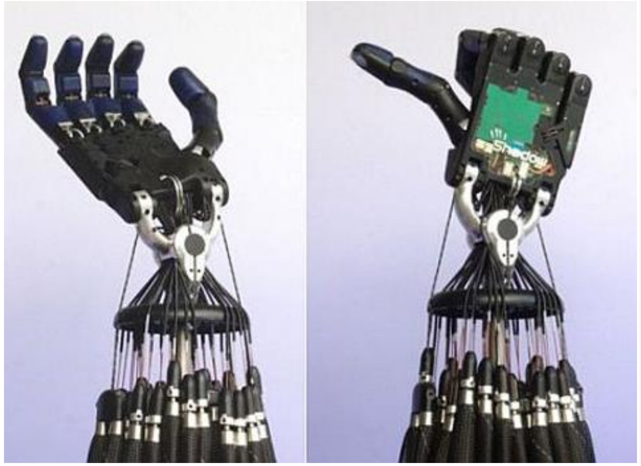
Literature

- Christopher Y. Brown and Harry Asada. **Inter-Finger Coordination and Postural Synergies in Robot Hands via Mechanical Implementation of Principal Components Analysis**, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), (2007)

Red: relevant for the exam

Building robot hands based on postural synergies

- Do we really need (want) to independently control more than 20 DoF in a robotic hand?
  - Example: Shadow hand, ARMAR hands, …



- Engineer's perspective:

  The more motors in the hand...

  ... the more expensive the hand

  ... the heavier the hand (load on the robot arm!)

  ... the harder to control

- A different approach:
  - Use only as many motors as necessary.
  - Use a mechanical implementation of postural synergies.

- This is part of a whole area of research: **underactuated hands**

Mechanical implementation of hand synergies

- Each desired posture (configuration) of the robot hand is represented by a posture vector:

$$\boldsymbol{P_i} = \left[z_1 \ldots z_j \ \ldots z_n\right]^T$$

- The elements z_j of the posture vector are the **linear tendon displacements** required to create the posture.

- Given N posture vectors, we define the posture matrix:

$$\boldsymbol{P} = \begin{bmatrix} \boldsymbol{P_1^T} \\ \vdots \\ \boldsymbol{P_i^T} \\ \vdots \\ \boldsymbol{P_N^T} \end{bmatrix}$$

Mechanical implementation of hand synergies

- Principal Components Analysis (PCA) lets us rewrite the posture matrix as the product of two smaller matrices:
  - one matrix consisting of the principal component vectors and
  - one matrix consisting of the weights for those vectors.

- Similar to singular value decomposition (see Brown and Asada 2007)
  - First, calculate the covariance matrix of $\boldsymbol{P}$.
  - Next, find the eigenvectors of the covariance matrix.
  - These are the principal components of $\boldsymbol{P}$. Their associated eigenvalues, ranked from largest to smallest, represent the relative importance of each component (i.e. the variance in the data explained by the respective component).
  - Since these principal components can be used to reconstruct the entire posture matrix, we call them eigenpostures.

Mechanical implementation of hand synergies

- If we choose to use only a few of the eigenpostures, then we can still approximate the posture matrix with reasonable accuracy.
- Here, we use only two principal components, so:
- $$\boldsymbol{P} \approx \widehat{\boldsymbol{P}} = \begin{bmatrix} q_{1,1} & q_{1,2} \\ & \vdots \\ q_{i,1} & q_{i,2} \\ & \vdots \\ q_{N,1} & q_{N,2} \end{bmatrix} \begin{bmatrix} \boldsymbol{e}_1^T \\ \boldsymbol{e}_2^T \end{bmatrix} + \begin{bmatrix} \bar{z}_1 & \cdots & \bar{z}_n \\ \bar{z}_1 & \cdots & \bar{z}_n \\ & \vdots & \\ & \vdots & \\ \bar{z}_1 & \cdots & \bar{z}_n \end{bmatrix}$$
- The values $q_{i,k}$ are scalar weights.
- The vectors $\boldsymbol{e}_k$ are the eigenpostures.
- The additional term on the right is a zero-offset common to all postures (the average posture in the set)

Mechanical implementation of hand synergies

- Now we can rewrite each posture vector as:

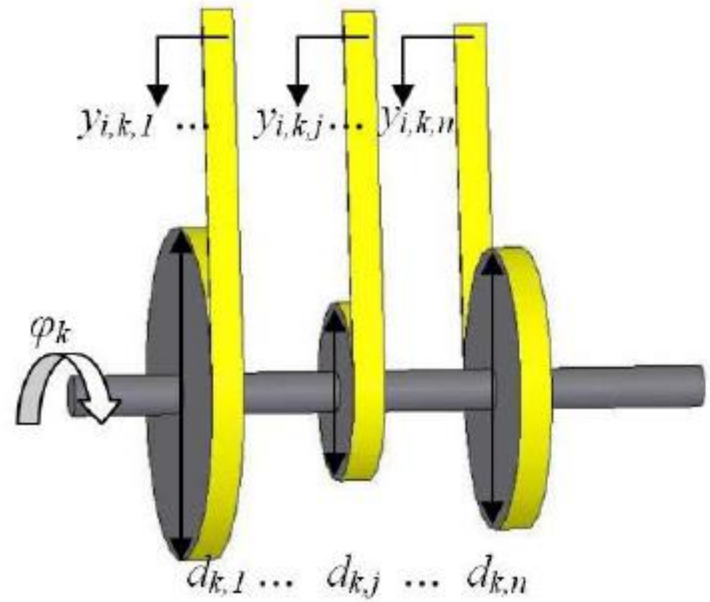
$$\boldsymbol{P_i} \approx q_{i,1}\boldsymbol{e_1} + q_{i,2}\boldsymbol{e_2} + \bar{\boldsymbol{z}}, \text{ where } \quad \bar{\boldsymbol{z}} = [\bar{z}_1 \dots \bar{z}_j \dots \bar{z}_n]$$

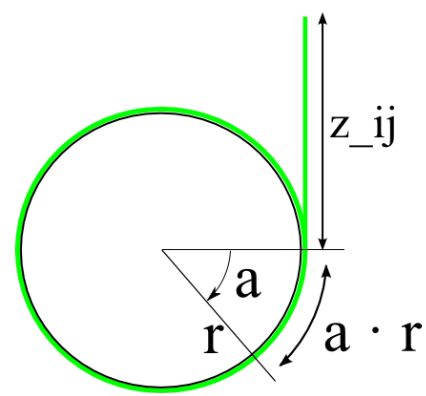
- **Goal: Find a way to realize this equation through mechanical means!**

- Problems to be solved in this context:
  - How to actuate a vector multiple $q_{i,k}e_k$?
  - How to mechanically add two vector quantities?
  - How to account for the zero offset $\bar{z}$?

How to actuate a vector multiple?

- We can use the individual elements of $\boldsymbol{e_k} = \left[d_{k,1} \dots d_{k,j} \;\dots d_{k,n}\right]$ as the diameters of pulleys fixed on a shaft (see figure)
- $q_{i,k}$ is represented in the angle of rotation of the shaft, $\Phi_{i,k} = 2q_{i,k}$.
- The tendon displacements $y_{i,k,j}$ equal the elements of $q_{i,k}\boldsymbol{e_k}$.
- If any of the values $d_{k,j}$ are negative, we can account for this by wrapping tendons in opposite directions.



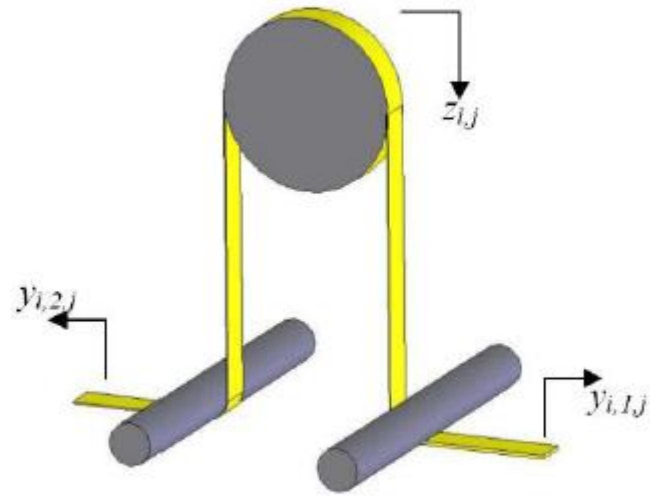


How to mechanically add two vector quantities?

- Add two scalar values by the mechanism in the figure.
- The pulley in the figure is free to translate in the vertical direction.
- This configuration also winds up scaling the output, so that: $z_{i,j} = \frac{1}{2}(\mathrm{y}_{\mathrm{i,1,j}} + \mathrm{y}_{\mathrm{i,2,j}})$
- Attach one of these mechanisms to each of the outputs $\mathrm{y}_{\mathrm{i,k,j}}$ from the mechanism on the previous slide.
- Then the vector output becomes:

$$[z_{i,1} \dots z_{i,n}] = \frac{1}{2}([\mathrm{y}_{\mathrm{i,1,1}} \dots \mathrm{y}_{\mathrm{i,1,n}}] + [\mathrm{y}_{\mathrm{i,2,1}} \dots \mathrm{y}_{\mathrm{i,2,}n}])$$

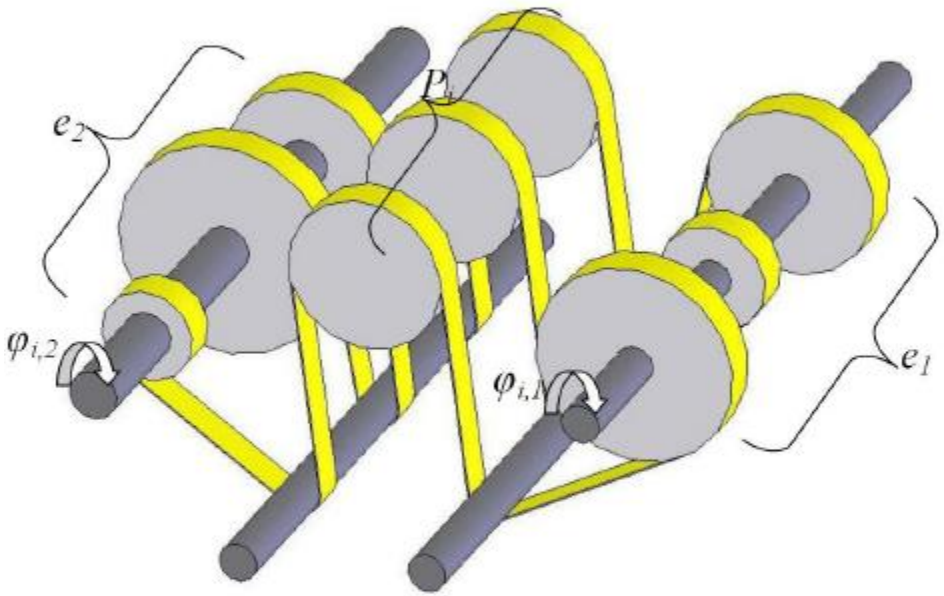
$$[z_{i,1} \dots z_{i,n}] = \frac{1}{2}(q_{i,1}\boldsymbol{e_1} + q_{i,2}\boldsymbol{e_2})$$



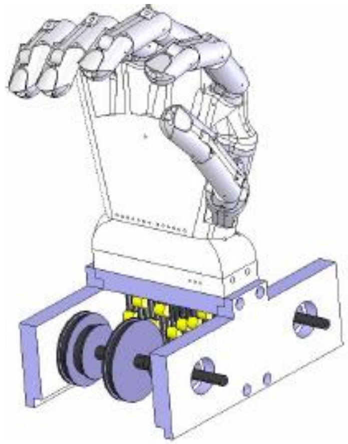
Putting everything together

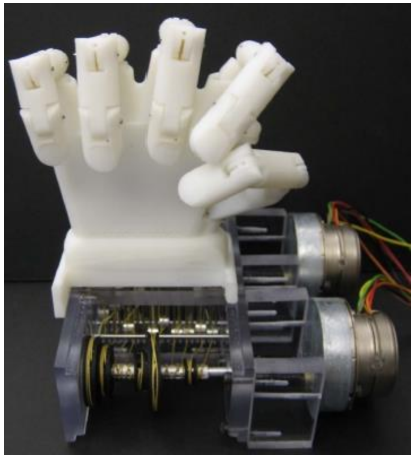
- How to account for the zero offset value $\bar{z}$?
  - Simply adjust the tendon lengths so that $[z_{i,1} \dots z_{i,n}] = \bar{z}$ when the shafts are in their zero position ($\Phi_1 = \Phi_2 = 0$)

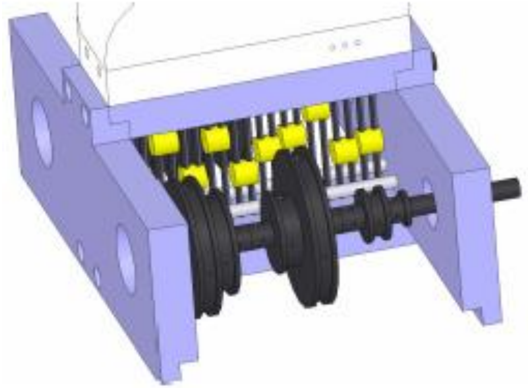
- The complete mechanism:

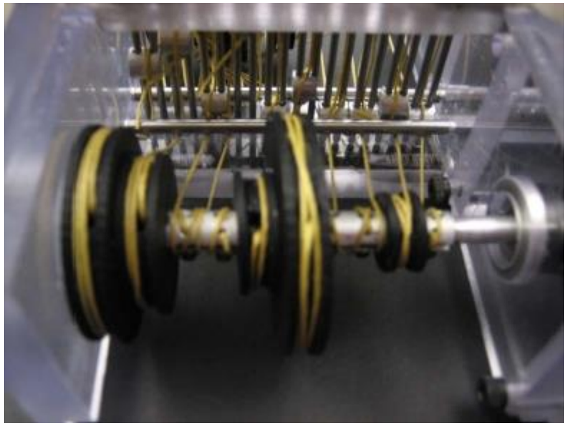


The resulting 17 DoF 5-fingered robot hand









The eigenposture mechanism

Sliding pulley details and tendon routing

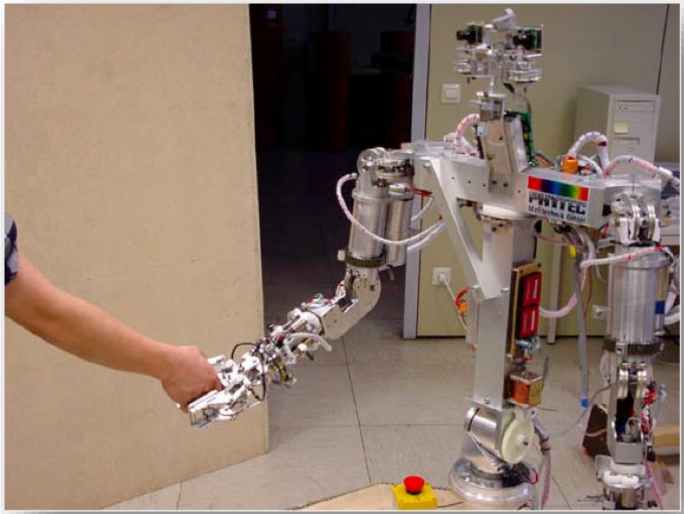
The TUAT/Karlsruhe Humanoid Underactuated Hand

Underactuation

- Underactuation expresses the property of a system to have an input vector of smaller dimension than the output vector
- In robotics, it means having fewer actuators than degrees of freedom (DoF)
  - Simple control
  - Adapt to the shape of the object
  - Mechanical intelligence

The TUAT/Karlsruhe Humanoid Underactuated Hand

- **It works with one actuator**



Humanoid Robot ARMAR
Univ. of Karlsruhe, Germany

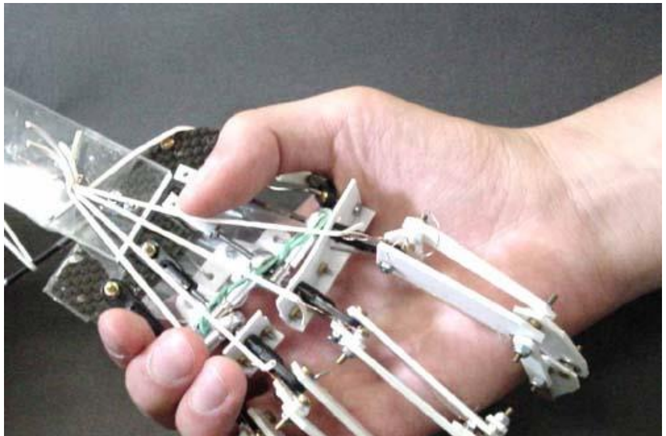
Artificial arm by using spherical ultrasonic motor

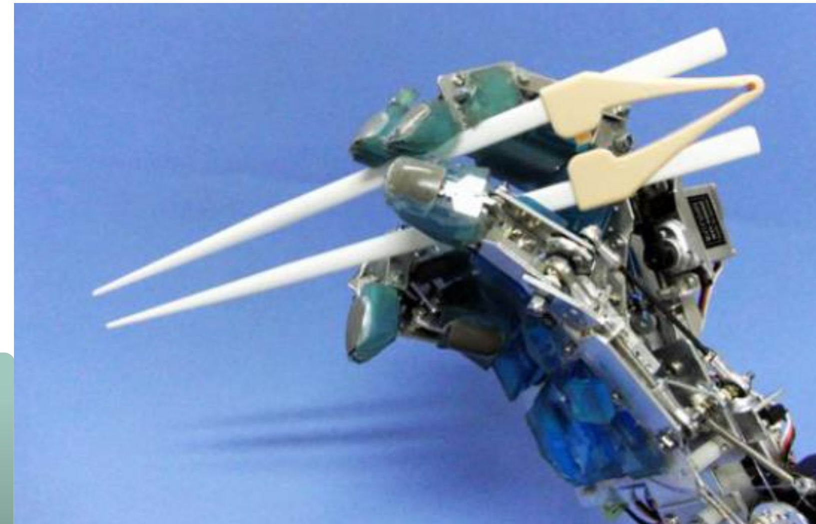
Tokyo Univ. of Agriculture and Technology
(東京農工大学／TUAT)

Joint work: Naoki Fukaya and Tamim Asfour

The TUAT/Karlsruhe Humanoid Hand

Karlsruhe Institute of Technology





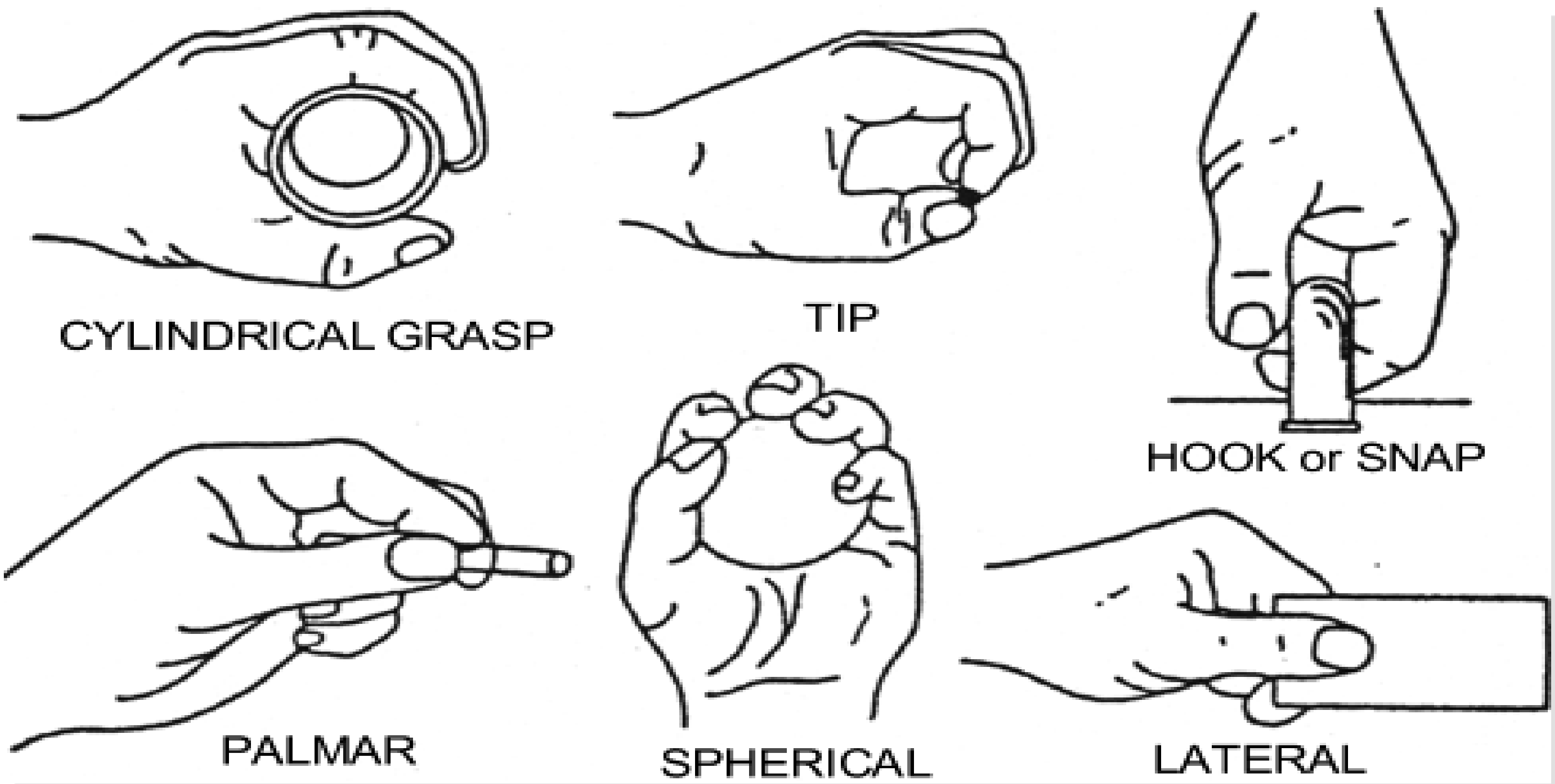
The core idea is the ”Mechanism”

1. Light weight, similar size, similar motion
2. Only one actuator
3. No need for sensors, simple operation
4. Self-make a best gripping shape
5. Self adjustment of fingertip force
6. No need for feedback control

H2T

The TUAT/Karlsruhe Humanoid Hand

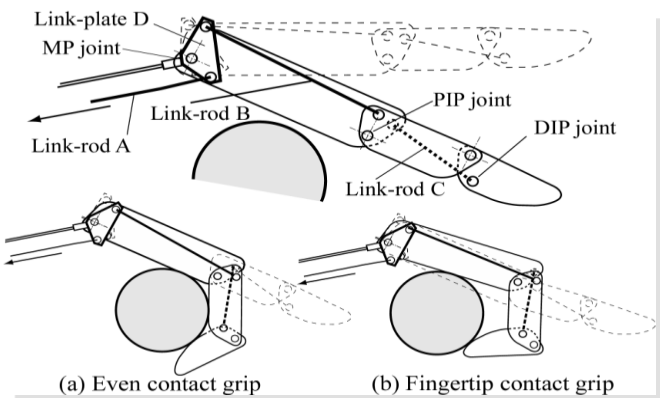
- Motivation: Typical grasp motion of daily life



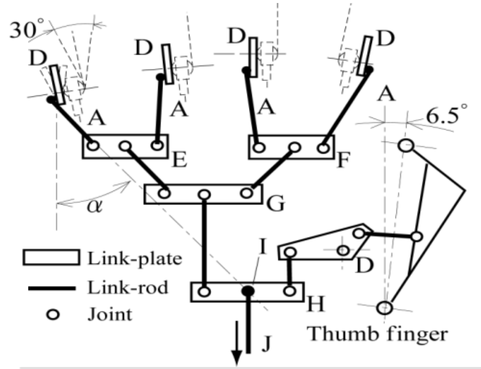
A. D. Keller, C. L. Taylor and V. Zahm: Studies to determine the functional requirements for hand & arm prostheses, Dept. of Engr., UCLA., CA, 1947

The TUAT/Karlsruhe Humanoid Hand

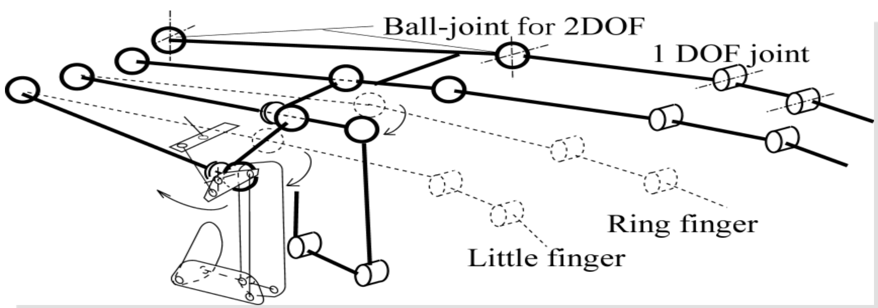
Finger link mechanism for finger



Self moving link mechanism for finger

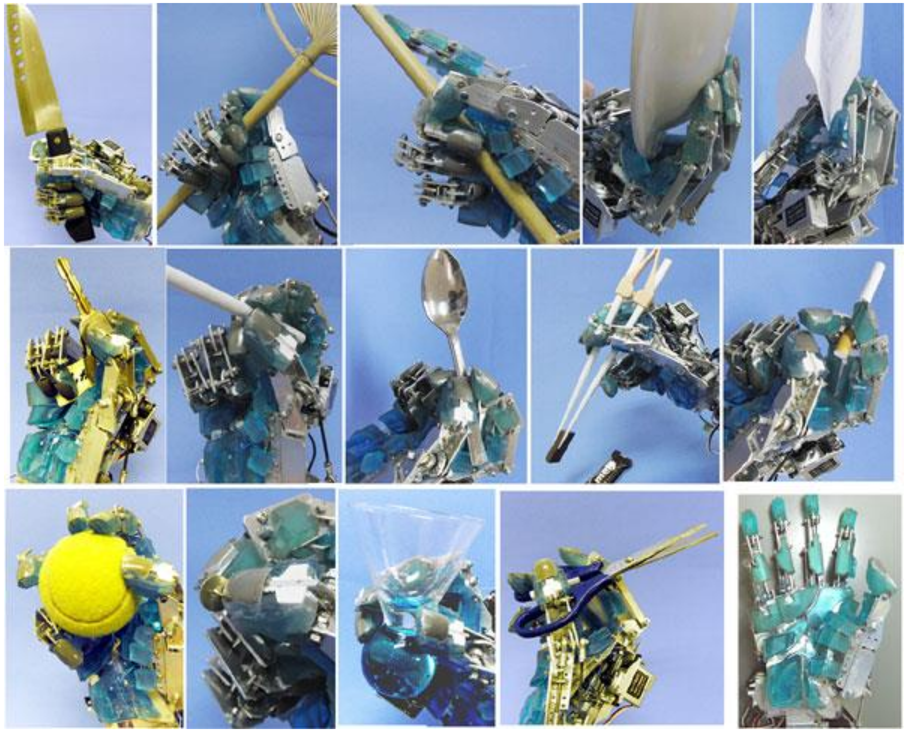


Palm moving mechanism



Latest version (2013)

- This hand realizes Cutkosky's taxonomy and 14 kinds of operations of daily life
- It operates by one large servo motor and 6 small auxiliary servo motors.
- Needs no feedback control, touch sensor and complex control system
- Easy operation (only push buttons of controller)



Naoki Fukaya, Tamim Asfour, Rüdiger Dillmann and Shigeki Toyama, Development of a Five-Finger Dexterous Hand without Feedback control: the TUAT/Karlsruhe Humanoid Hand, IROS 2013

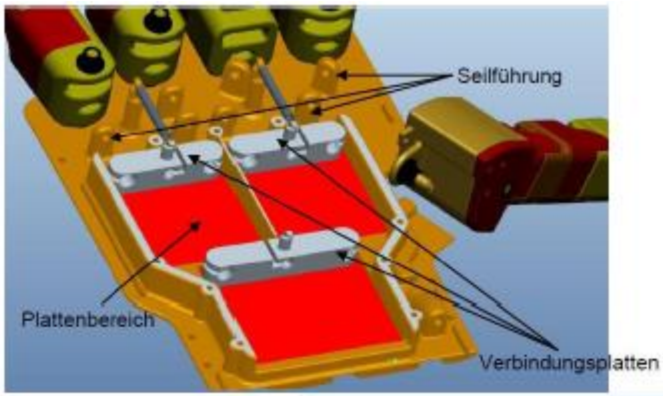
Red: relevant for the exam

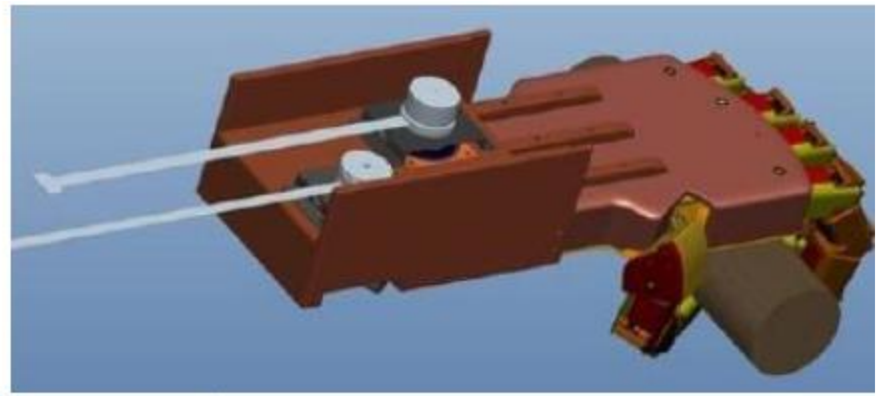
The TUAT/Karlsruhe Humanoid Hand

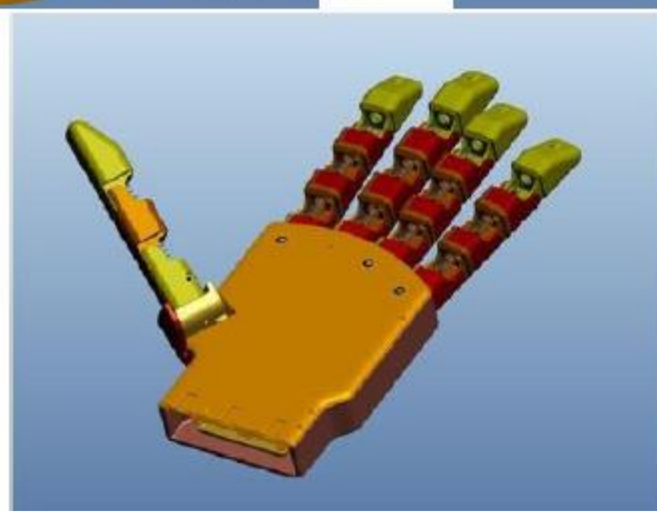
- Further development by Naoki Fukaya

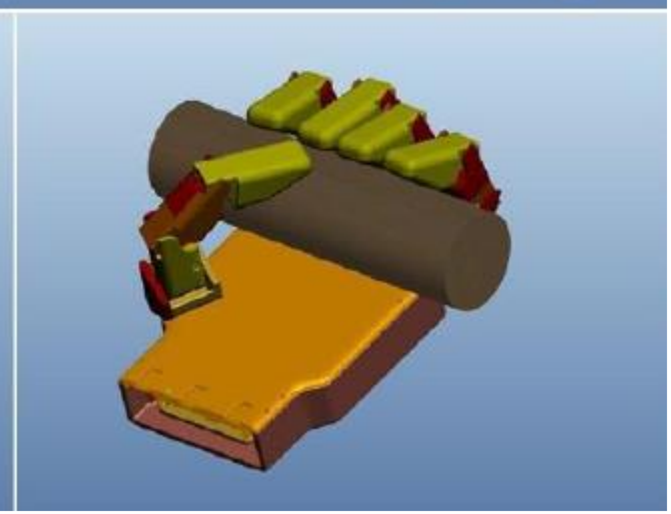
The TUAT/Karlsruhe Humanoid Hand

- Further development by Tamim Asfour for 3D printing



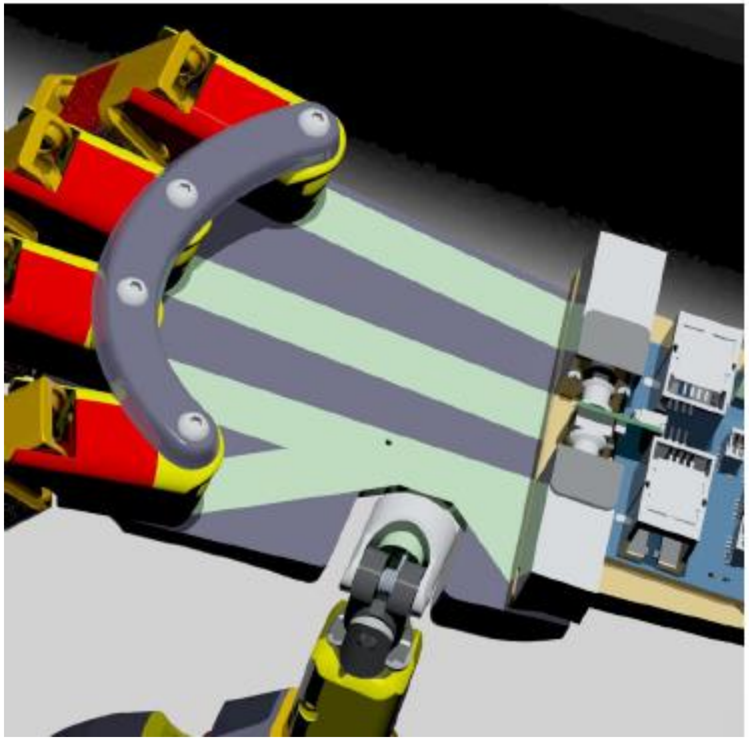


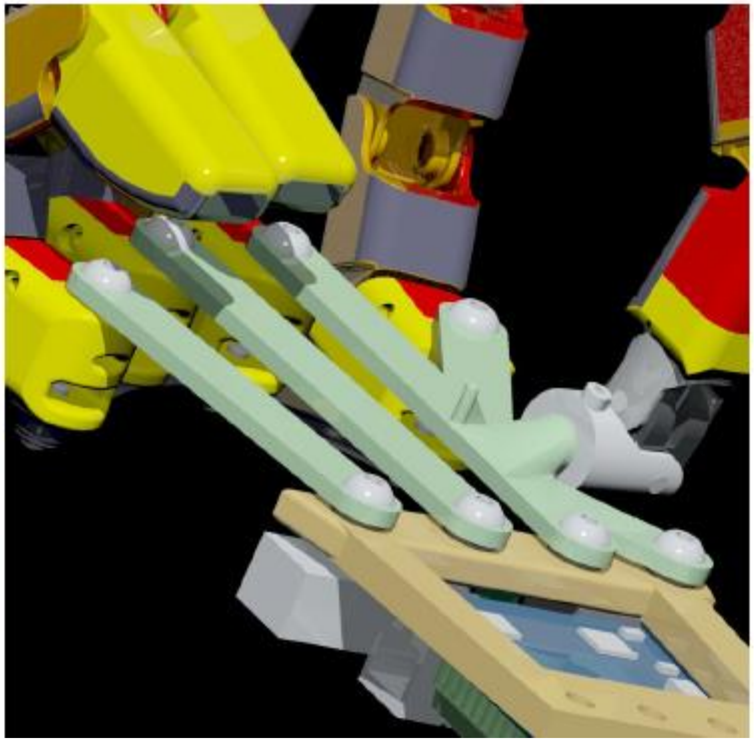




The TUAT/Karlsruhe Humanoid Hand

- Further development by Tamim Asfour for 3D printing





The TUAT/Karlsruhe Humanoid Hand

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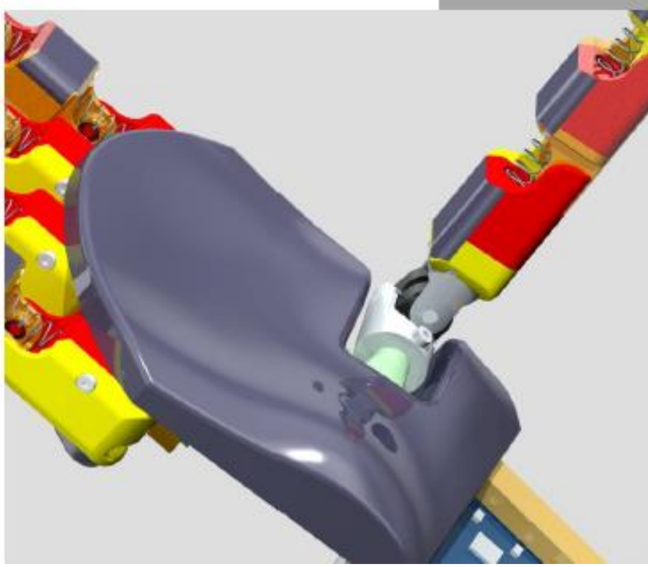

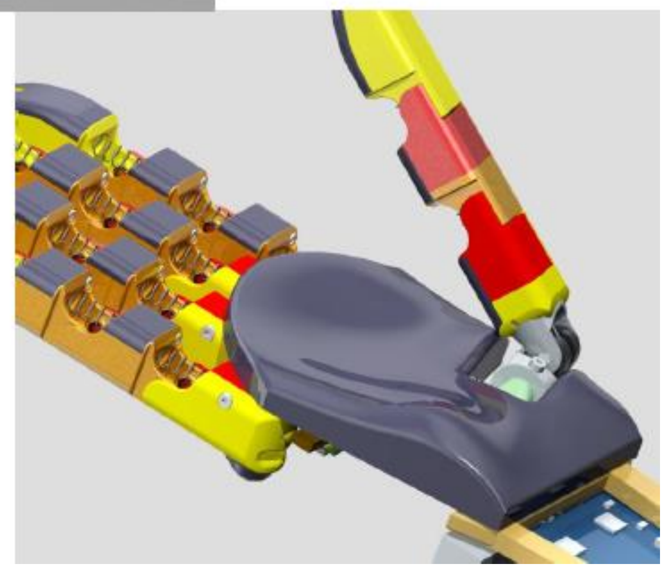

The TUAT/Karlsruhe Humanoid Hand

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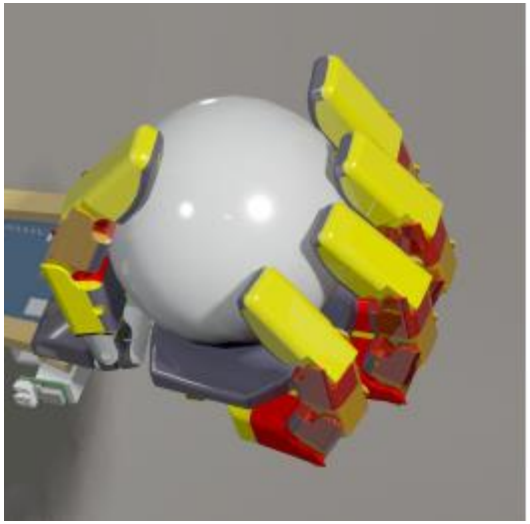
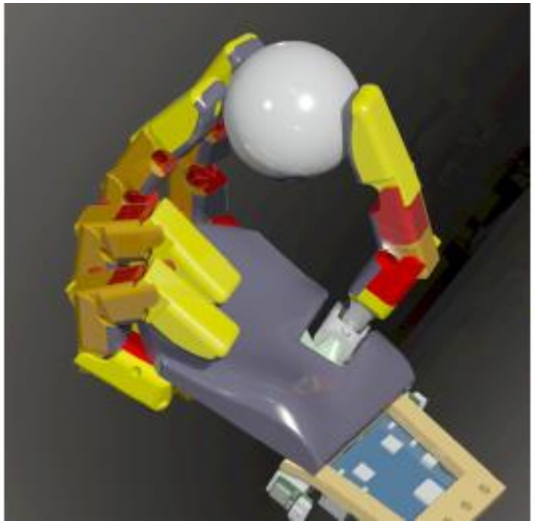
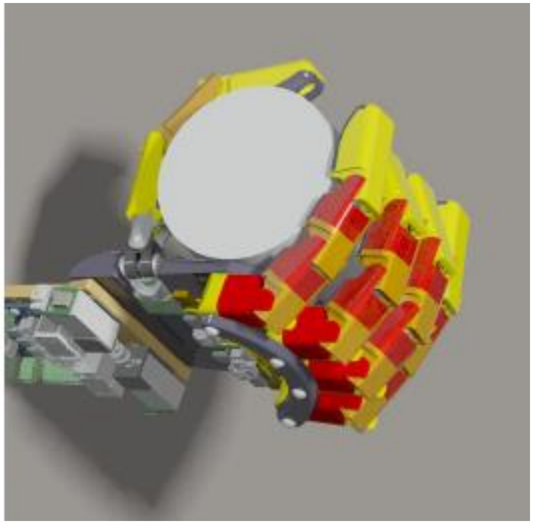
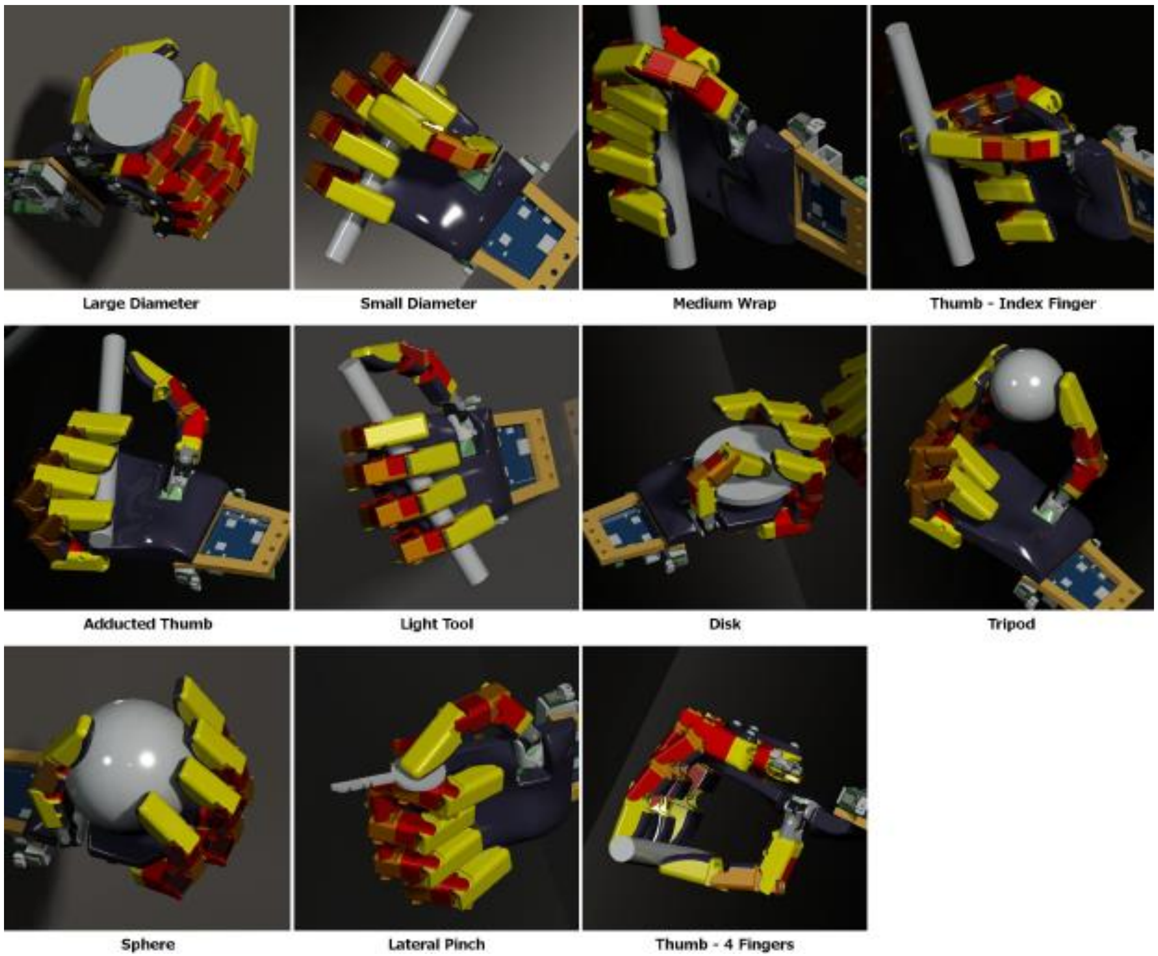




The TUAT/Karlsruhe Humanoid Hand

- Further development by Tamim Asfour for 3D printing



The TUAT/Karlsruhe Humanoid Hand

- Publications
  - Naoki Fukaya, Tamim Asfour, Rüdiger Dillmann and Shigeki Toyama, ***Development of a Five-Finger Dexterous Hand without Feedback control: the TUAT/Karlsruhe Humanoid Hand***, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2013)
  - Naoki Fukaya, Tamim Asfour, Rüdiger Dillmann and Shigeki Toyama, *Design of a Humanoid Hand for Human Friendly Robotics Applications.* International Conference on Machine Automation (ICMA2000).
  - Naoki Fukaya, Tamim Asfour, Rüdiger Dillmann and Shigeki Toyama, *Design of the TUAT/Karlsruhe Humanoid Hand.* IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2000)

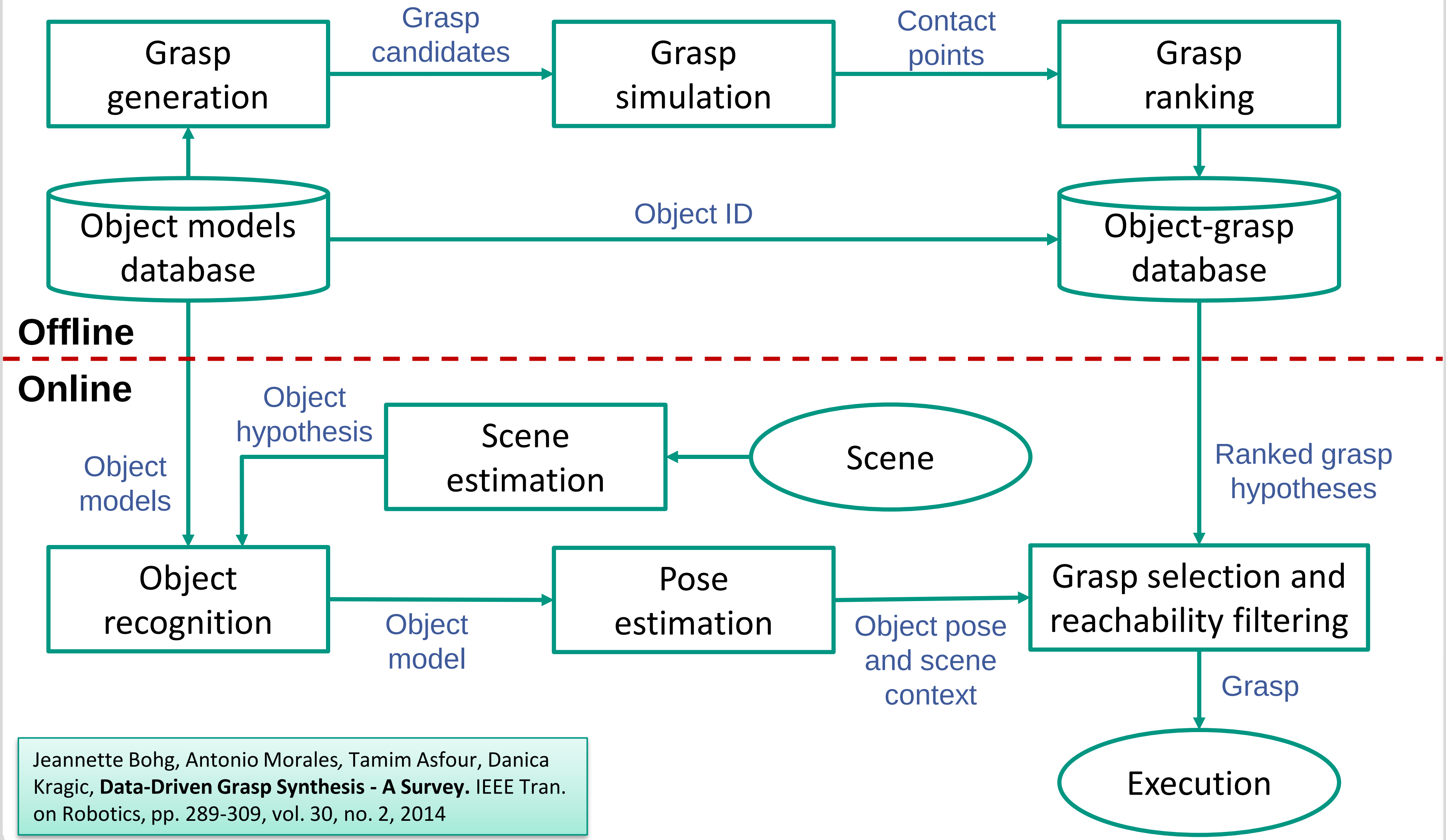
Red: relevant for the exam

Grasping known, familiar and unknown objects

Grasping Objects: Outline

- Grasping known objects: Recap
- Grasping familiar objects
  - Concepts
  - Different approaches
  - Part-based grasp planning for familiar objects
- Grasping unknown objects
  - Concepts
  - Approximating unknown object shape
  - From low-level features to grasp hypotheses

Grasping Known Objects: Typical Flow-Chart

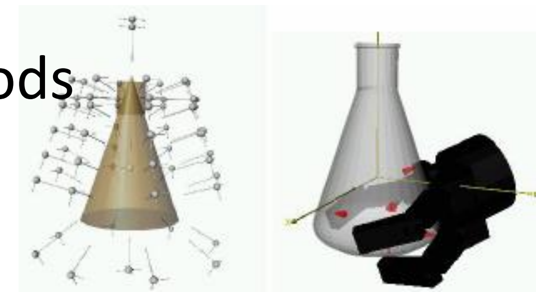


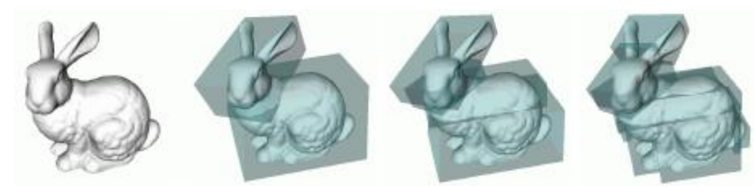
Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

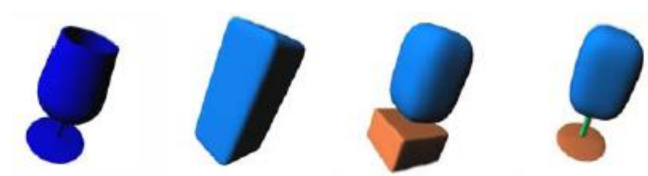
Known: Grasp Synthesis on Object Parts

- **Question**: How to generate good grasp candidates?

- Approaches for different segmentation methods
  - **Shape primitives**
    Manual segmentation into primitives
    (e.g. boxes, cylinders, spheres, cones)
  - **Box decomposition**
    Automatic segmentation into boxes
  - **Superquadrics**
    Automatic segmentation into superquadrics
  - **Medial axis transformation**
    Use only spheres
  - **Surface normals**



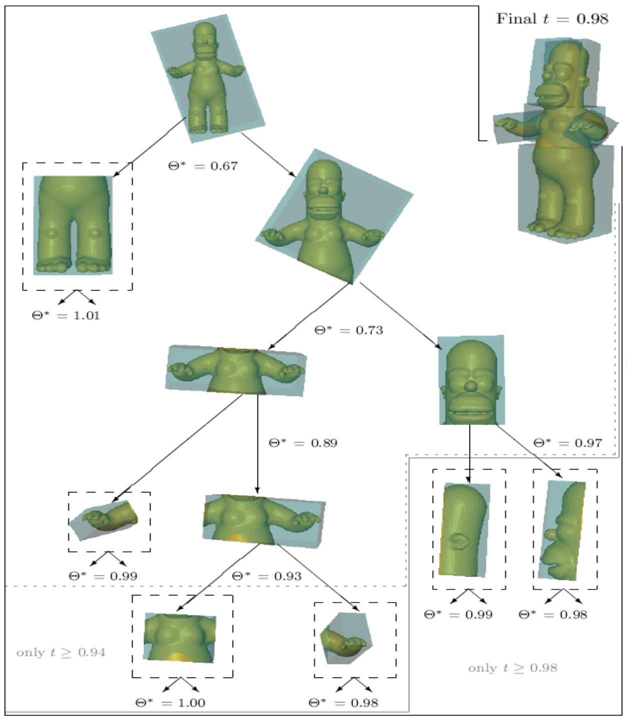




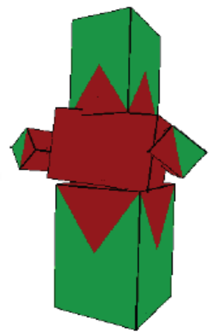
Part of Robotics-1

A Box-Based Approach: Concept

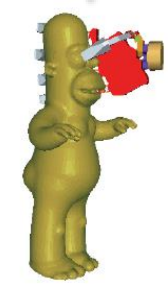
- **Approximate** the object's geometry with boxes (box decomposition)
- Generate **grasp hypotheses** for boxes
- **Evaluate** the grasp hypotheses



approximation of object geometry

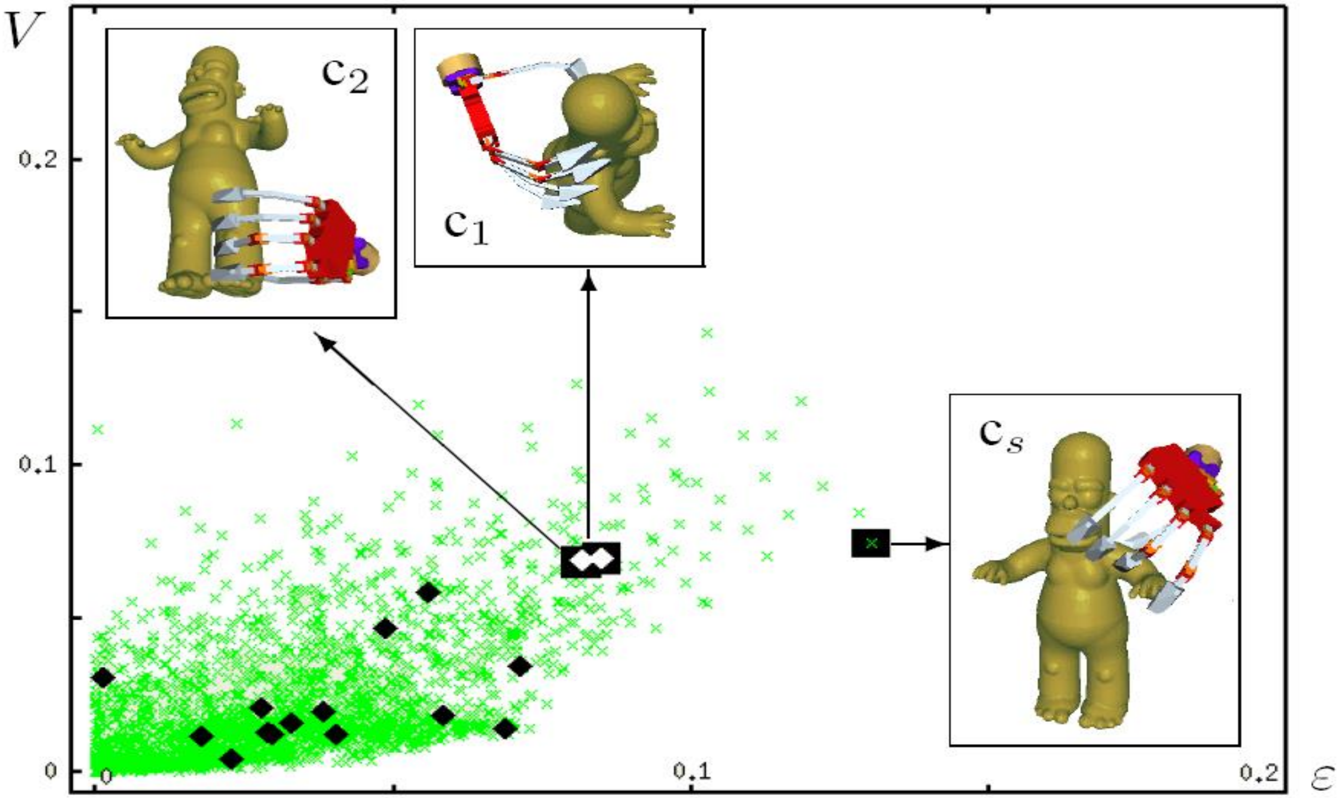


heuristic grasp selection



final grasp

A Box-Based Approach: Evaluation



Box decomposition generates few but high-quality grasp hypotheses

× Sample of spherical grasp
× "Best" spherical grasp
◆ Sample of box grasp
◇ "Best" box grasp(s)

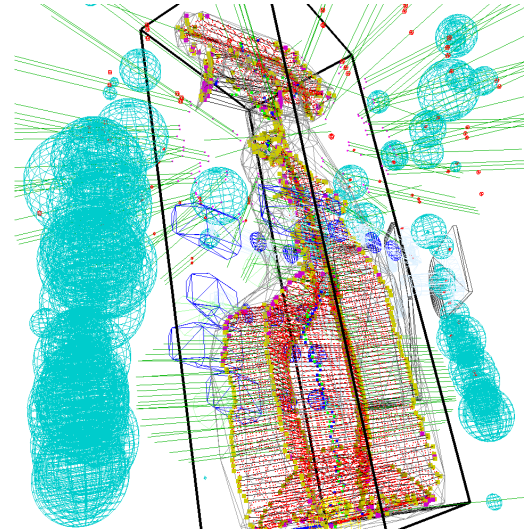
Huebner, K., Welke, K., Przybylski, M., Vahrenkamp, N., Asfour, T., Kragic, D., and Dillmann, R. **Grasping Known Objects with Humanoid Robots: A Box-Based Approach**. In 14th International Conference on Advanced Robotics, 2009

Grasp Planning using Medial Axis: Concept

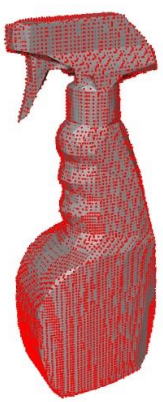
- Medial axis
  - Approximate object form using contained spheres with maximal diameter
  - Contained spheres must touch the object surface at two or more points
- The medial axis
  - is the **union of the centers** of all contained spheres
  - Describes the **topological skeleton** of the object
- Advantages
  - Good approximation of object geometry
  - Details are retained
  - Good description of symmetries

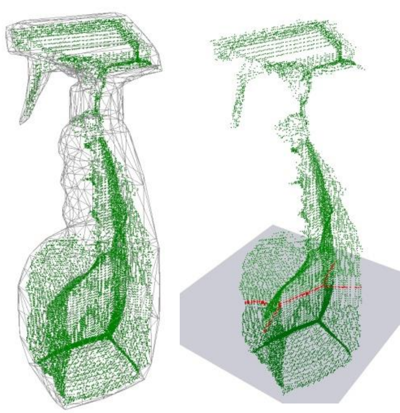
H. Blum, **Models for the Perception of Speech and Visual Form**. Cambridge, Massachusetts: MIT Press, 1967, A transformation for extracting new descriptors of shape, pp. 362–380.

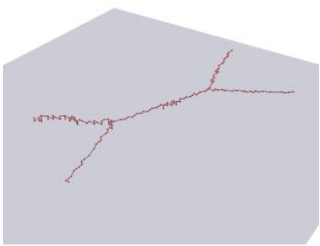
Grasp Planning using Medial Axis: Algorithm

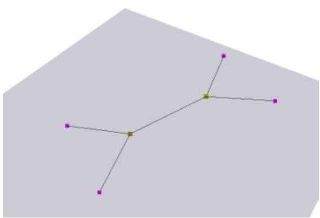


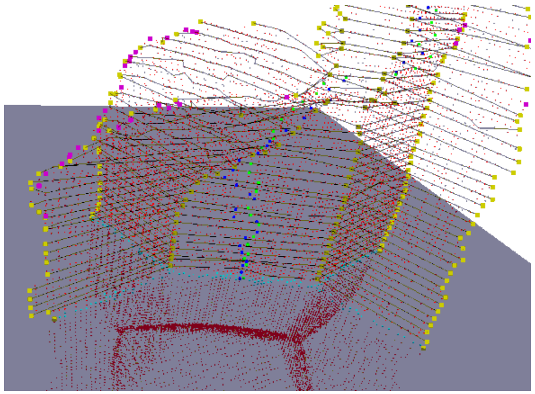
- Sample object surface
- Calculate medial axis
- Analyze the cross-section of the medial axis
  - Minimum Spanning Tree
  - Clustering
  - Convex hull
- Generate grasp hypotheses
- Evaluate grasp stability

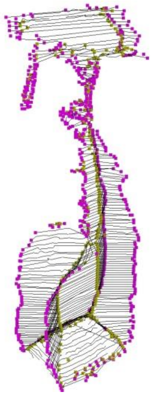












Przybylski, Markus, Tamim Asfour, and Rüdiger Dillmann. **Planning grasps for robotic hands using a novel object representation based on the medial axis transform**. IROS, 2011.

Grasping Familiar Objects: Concept

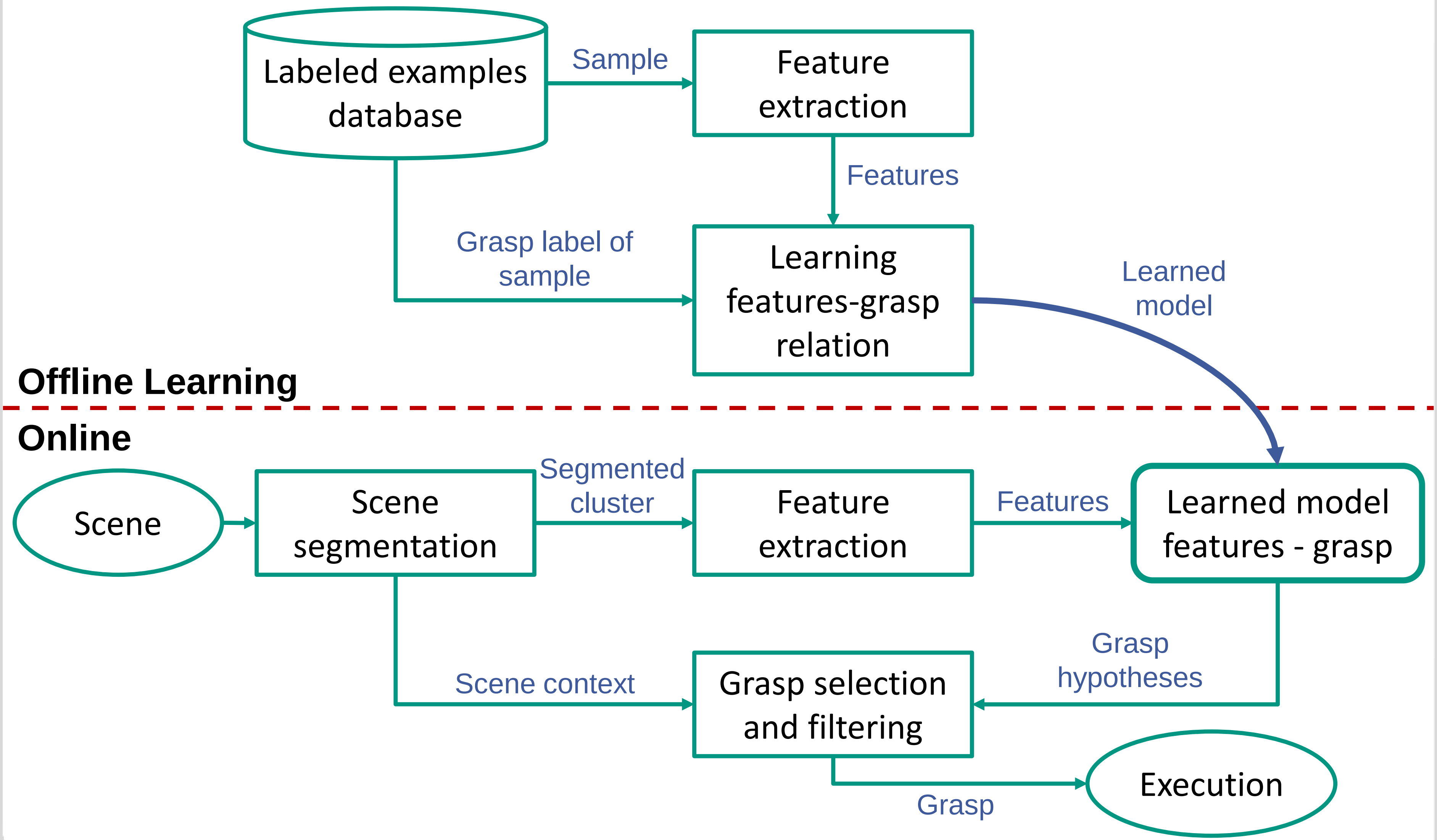
- Identify categories of objects with **common characteristics/features**
  - Visual: texture, shape, spatial constellation
  - Semantic: Functionality, task
- Train grasps on a set of **known objects**
  - Store features and generated grasps
  - Use learning mechanisms for generalization
- Grasp new but **familiar objects**
  - Categorize the new object
  - Recall grasp hypothesis of objects in the same category
  - Adapt grasp hypothesis to new object
- Optional: Update database with new data

Grasping Familiar Objects: Approaches

- Discriminative approaches
  - Learn a discriminative function to distinguish bad and good grasps
  - Use low-level 2D and/or 3D features
- Grasp synthesis by comparison
  - Find the most similar object in the database
  - Adapt good grasps from that object
- Generative models for grasp synthesis
  - Abstract over all examples in the database
- Category-based grasp synthesis
  - Use object categories and semantic to determine similarity

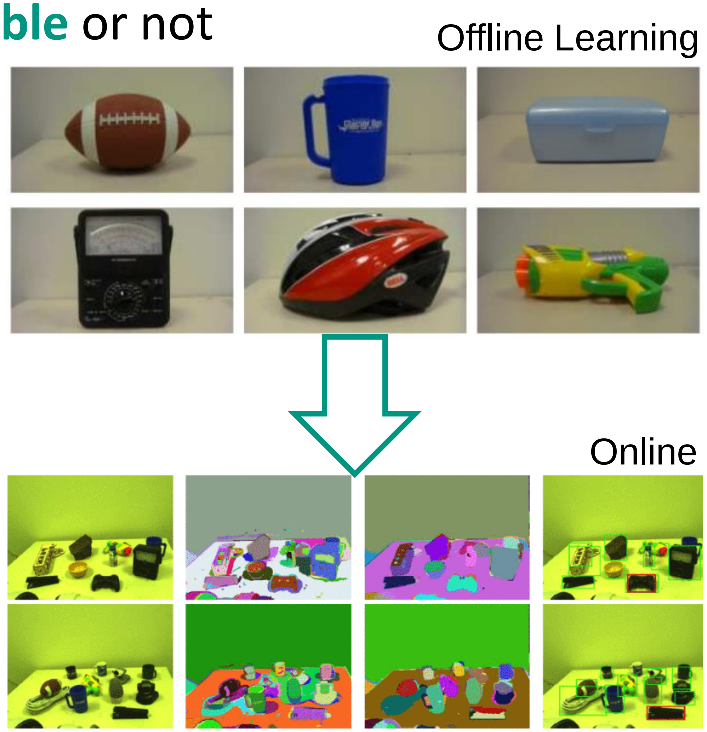
Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

Discriminative Approaches: Flow-Chart



Discriminative Approaches: Rao et al.

- Goal: Learn which parts of the scene are **graspable** or not
- Preprocessing:
  - Segment based on depth information
- Feature vector
  - Color information (LAB color space)
  - Variance in depth and height of segments (3D)
  - Width and height of segments (2D)
- Learning mechanism
  - Support Vector Machine (SVM) with Gaussian Radial Basis Function (RBF) kernel



D. Rao, Q. V. Le, T. Phoka, M. Quigley, A. Sudsang, and A. Y. Ng, **Grasping novel objects with depth segmentation**, in Proc. IEEE/RSJ, Int. Conf. Intell. Robots Syst., 2010

Grasp Synthesis by Comparison

- General:
  - Find the most similar object (part) in the database
  - Use the associated grasps to generate good grasp hypotheses

- Synthetic exemplars:
  - Requirement: 3D object models (for exemplary and familiar objects)
  - Use 3D models to calculate similarity
  - Transfer grasp to familiar object

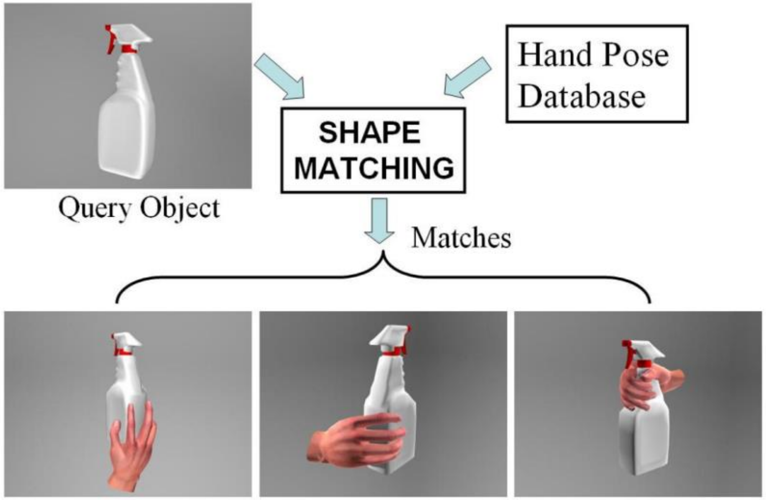
- Sensor-based exemplars:
  - Use object representation from sensor data
  - Execute on real robot
  - Learn from past and new grasp experiences

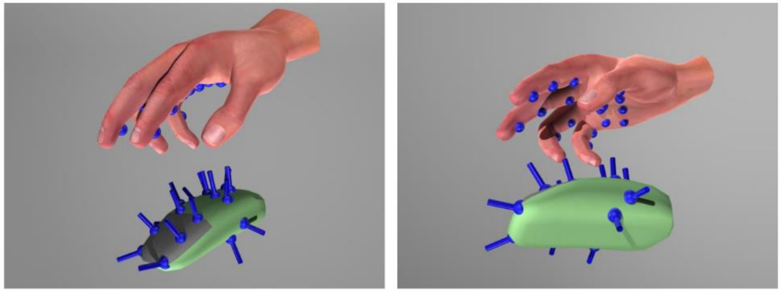
Synthetic Exemplars: Li and Pollard

- Grasp synthesis as a **shape matching** problem
  - Offline: Fill hand pose database
  - Online: query matching hand pose

- Hand pose database
  - **Contact points** and **normals**
  - On hand and known object

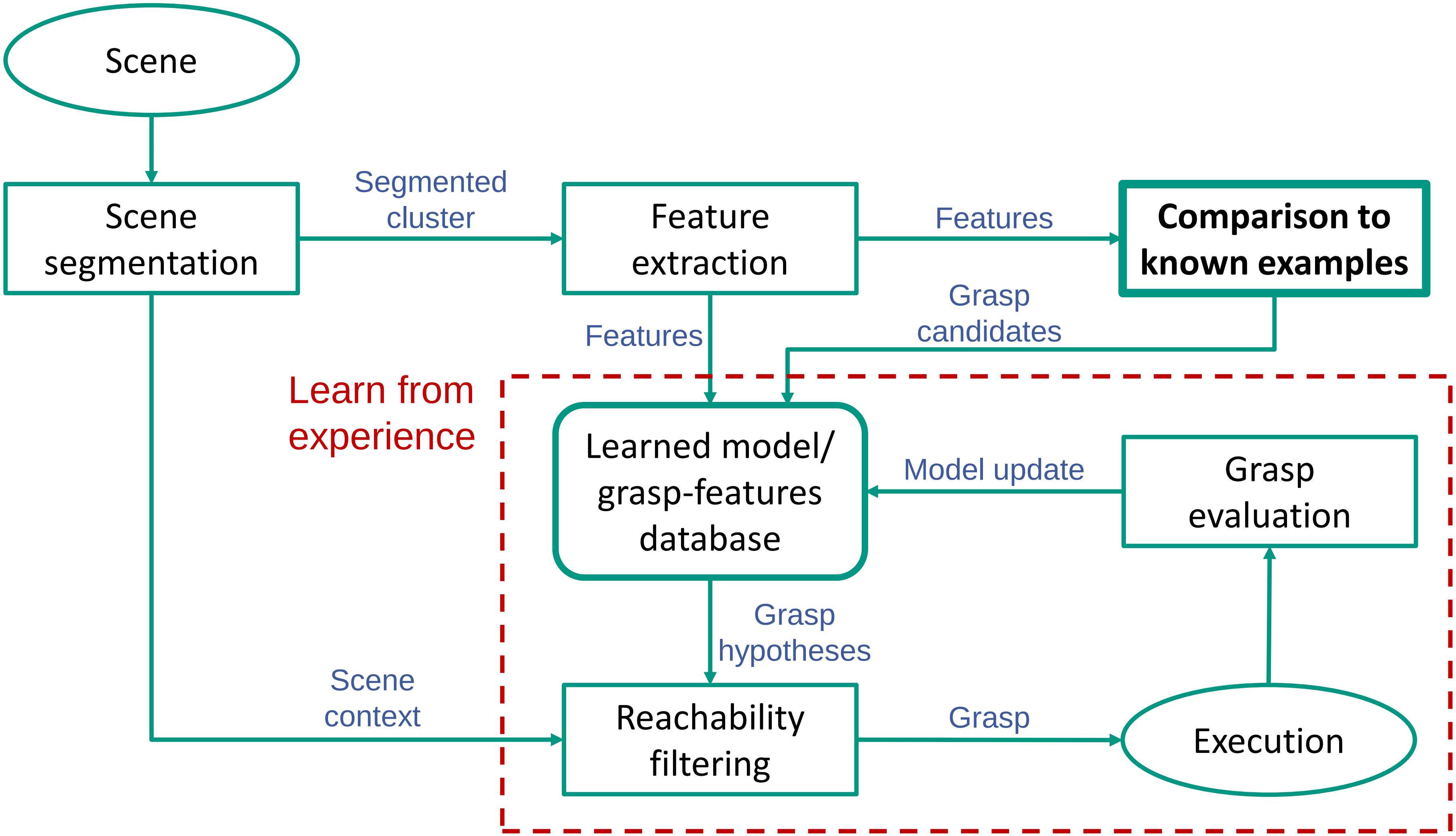
- Shape matching process
  - Query: new object model
  - Find: Hand pose with matching/similar contact points and normals





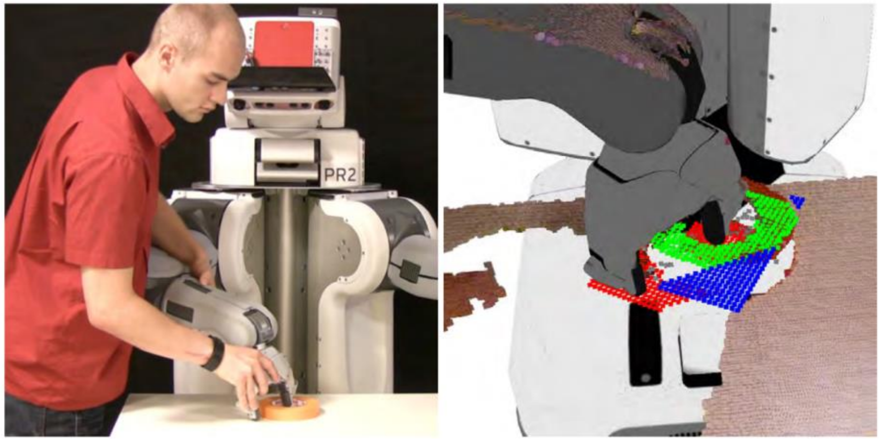
Y. Li and N. Pollard, **A Shape Matching Algorithm for synthesizing humanlike enveloping grasps**, in Proc. IEEE/RAS Int. Conf. Human. Robots (Humanoids), Dec. 2005, pp. 442–449.

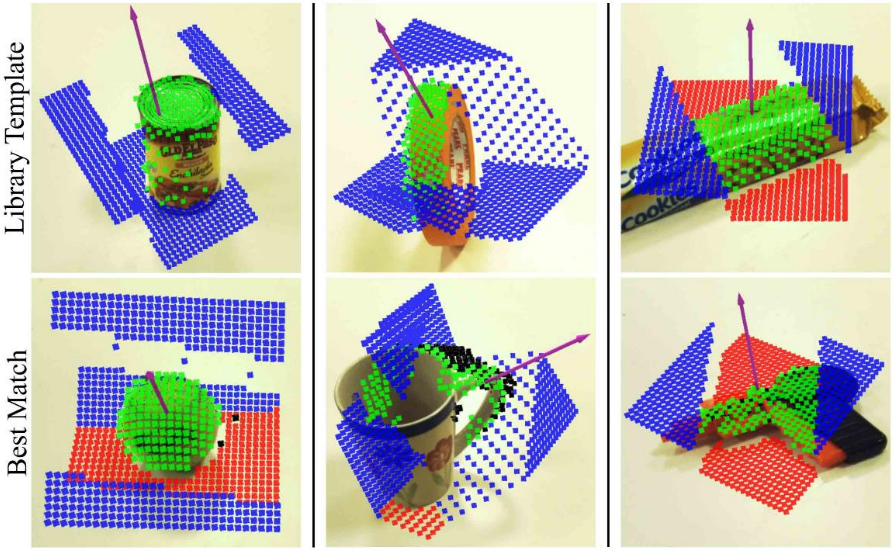
Sensor-Based Exemplars: Flow-Chart



Sensor-Based Exemplars: Herzog et al.

- Training data
  - Programming by demonstration
  - Generate templates from **demonstrated grasps**
- Template
  - **Local shape descriptor** for a possible grasp pose
  - Generated from 3D depth data
- Matching
  - Find **best matching template** according to the local shape

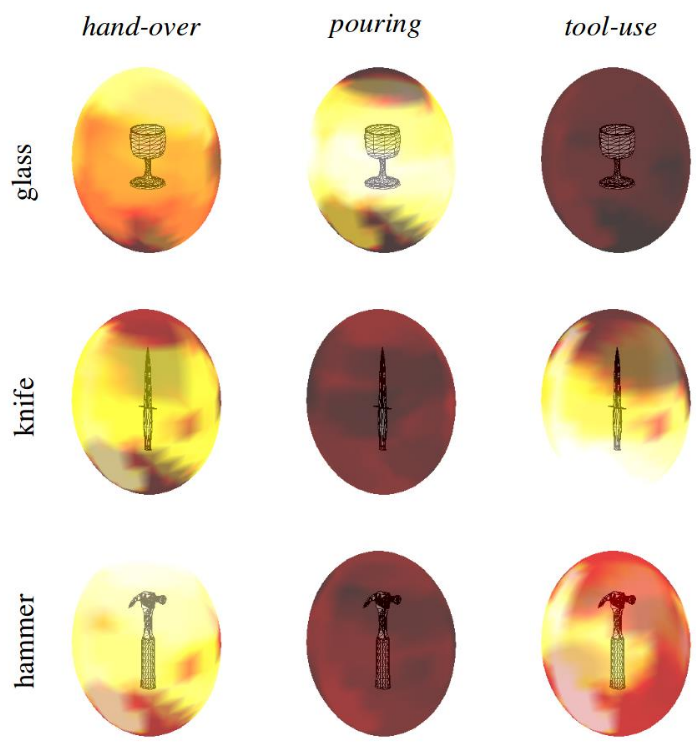




A. Herzog, P. Pastor, M. Kalakrishnan, L. Righetti, T. Asfour, and S. Schaal, **Template-based learning of grasp selection**, in Proc. IEEE Int. Conf. Robot. Autom., 2012, pp. 2379–2384.

Generative Models for Grasp Synthesis: Song et al.

- Infer grasp configuration for an object given a **specific task**
- Joint distribution of variables is modelled as **Bayesian network**
- Training data:
  - Grasp examples generated in GraspIt!
  - Annotated with task-specific quality metrics
- Improved structure learning
  - Nonlinear dimensionality reduction



Ranking of approach vectors
Brighter: Higher rank

D. Song, C. H. Ek, K. H˙ ubner, and D. Kragic, **Multivariate discretization for bayesian network structure learning in robot grasping**, in Proc. IEEE Int. Conf. Robot. Autom., Shanghai, China, May 2011, pp. 1944–1950.

Category-Based Grasp Synthesis

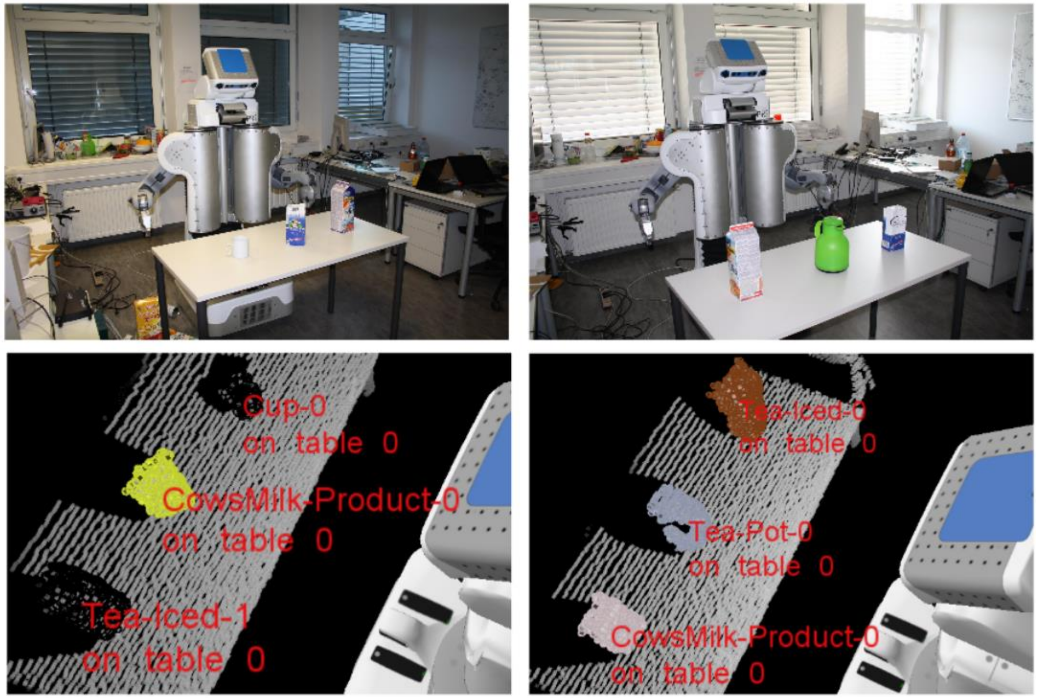
- Previous approaches:
  - Similar low-level features → Similar grasp

- Idea: Similarity on **semantic level**
  - Different shape or appearance
  - Same functional category
  - But can be grasped in a similar way

- Category is not known
  - Category needs to be determined
  - **Classification of objects** based on features

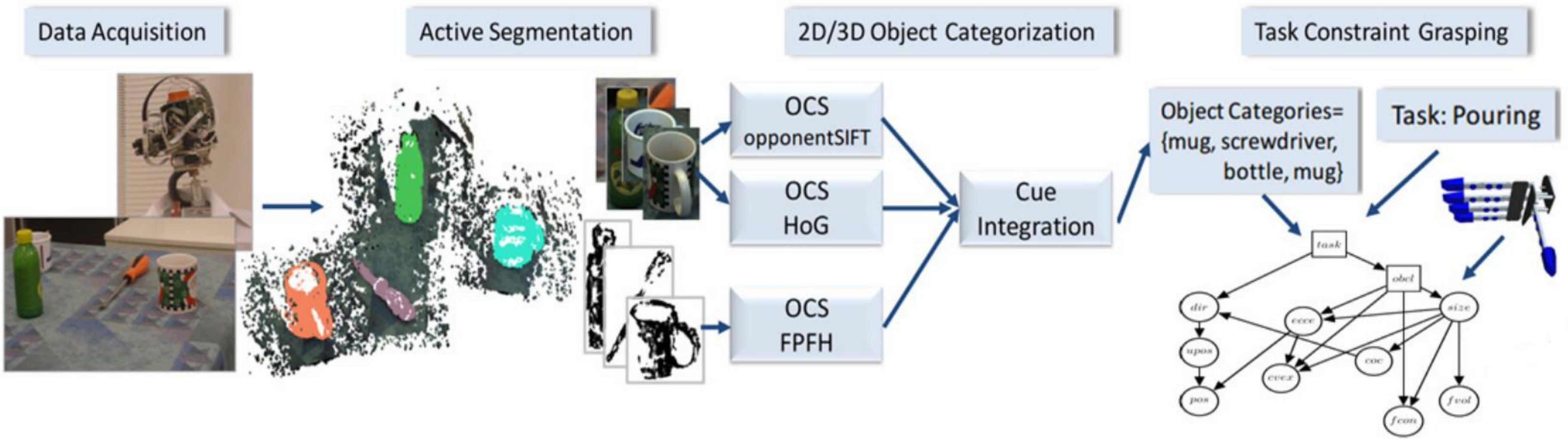
Category-Based Grasp Synthesis: Marton et al.

- Features based on
  - Segmented point cloud
  - Segmented image region
- Object classification
  - Bayesian network
  - Fixed set of categories
- Only detection of categories
  - No grasp synthesis



Z. C. Marton, D. Pangercic, N. Blodow, and M. Beetz, **Combined2-D–3-D categorization and classification for multimodal perception systems**, Int. J. Robot. Res., vol. 30, no. 11, pp. 1378–1402, 2011.

Category-Based Grasping: Madry et al.



- Classification based on multi-model visual descriptors
- Also uses task information
- Bayesian network generates hand configuration

M. Madry, D. Song, and D. Kragic, **From object categories to grasp transfer using probabilistic reasoning**, in Proc. IEEE Int. Conf. Robot. Autom., 2012, pp. 1716–1723.

Part-Based Grasp Planning for Familiar Objects

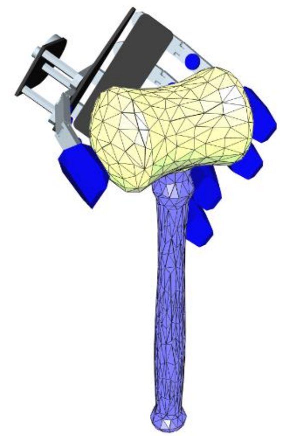
- Goal
  - **Generalized grasping information** for familiar objects
  - Grasps can be used for familiar objects and **partly known objects**
- Offline learning
  - **Train** grasps on multiple familiar object models
  - Identify promising grasps with **transferability success measure**
- Online
  - **Transfer** grasps to similar novel objects

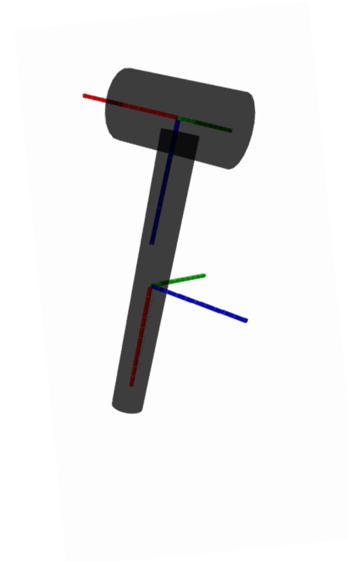
Vahrenkamp, Nikolaus, et al., **Part-based grasp planning for familiar objects**, Humanoid Robots (Humanoids), 2016 IEEE-RAS 16th International Conference on. IEEE, 2016.

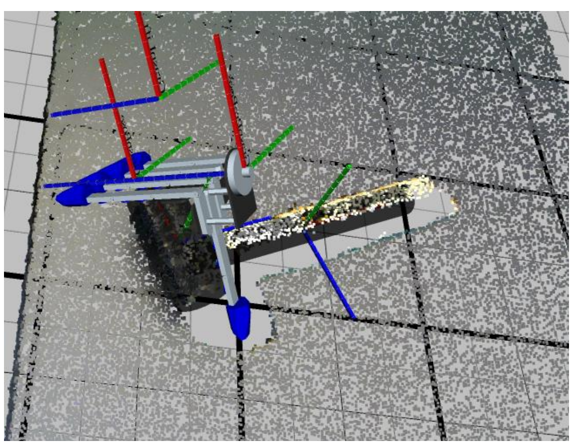
Part-Based Grasp Planning for Familiar Objects

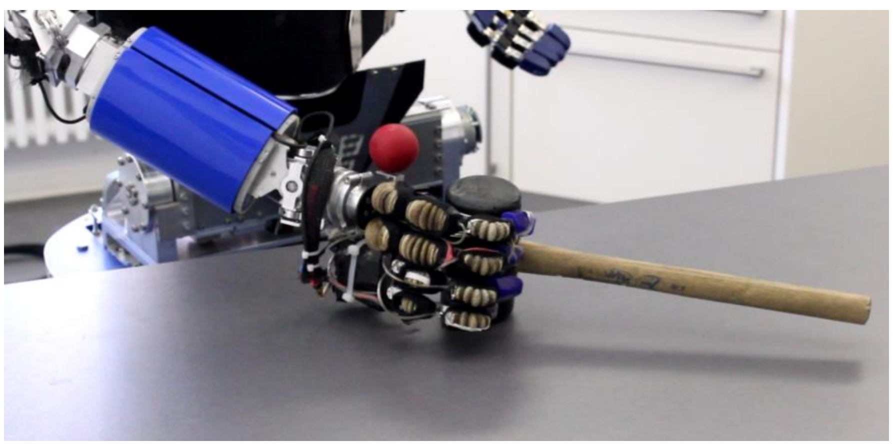
- Offline learning
  - Step 1: Object Shape Segmentation
  - Step 2: Labeling with task-based information
  - Step 3: Part-based grasp planning

- Online execution
  - Localization and approximation of object parts
  - Grasp transfer to novel object

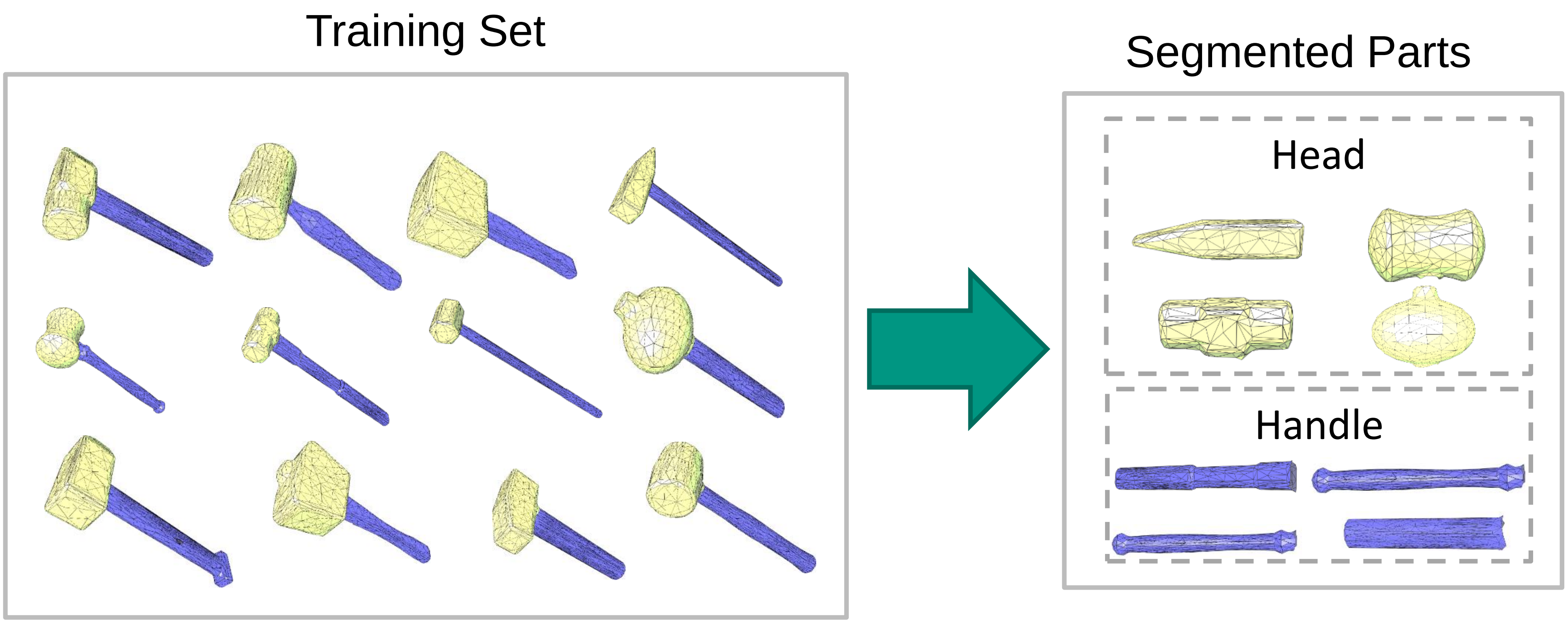








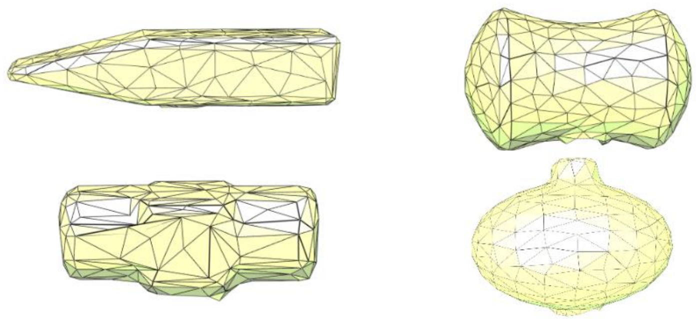
Offline Step 1: Object Shape Segmentation



Offline Step 2: Labeling with Task-Based Information

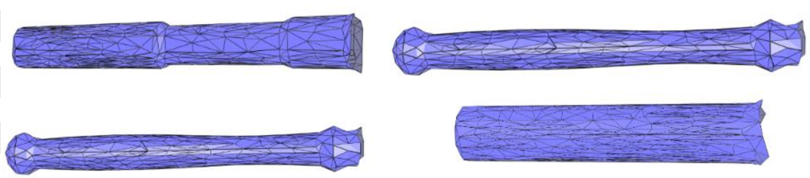
Segmented Parts

Head



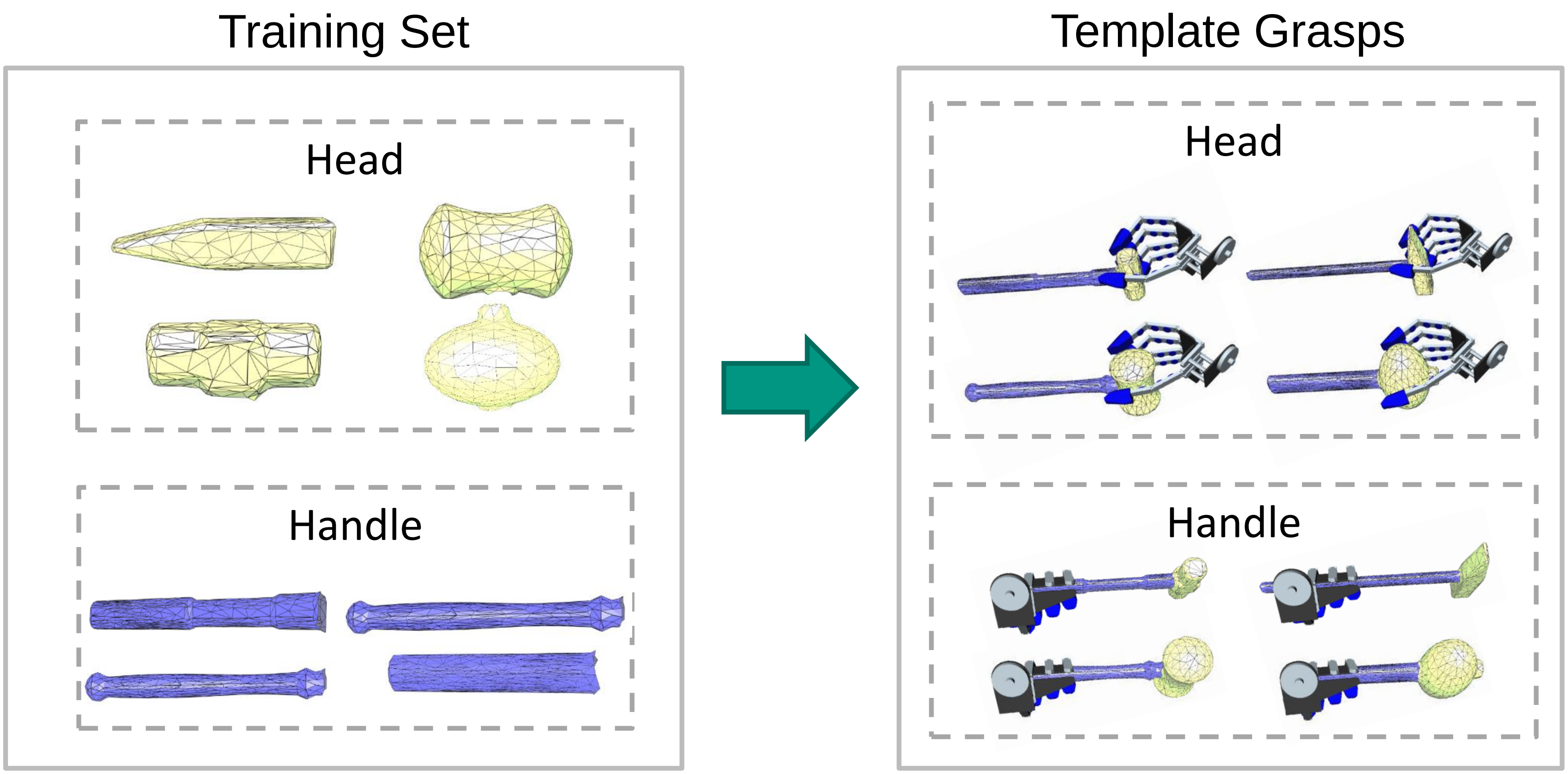
Task: hand over

Handle



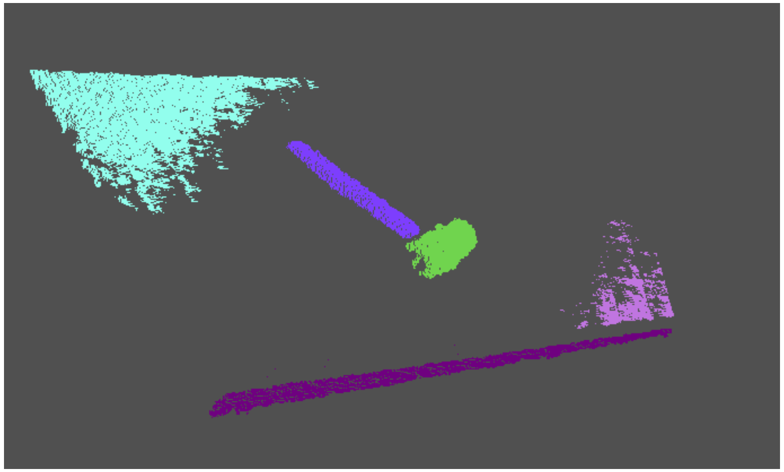
Task: tool use

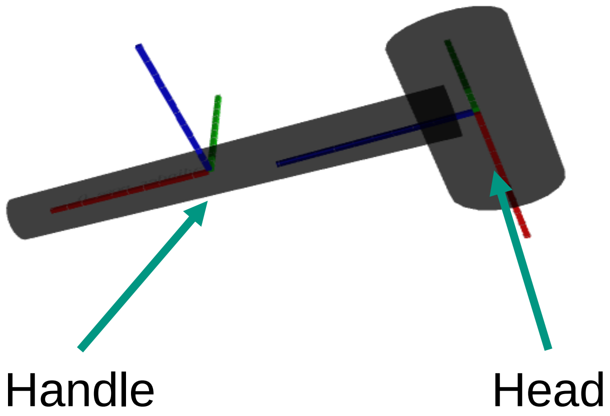
Offline Step 3: Part-Based Grasp Planning



Online: Localization and Approximation of Object Parts

- Input: RGBD data (point cloud)
- Segmentation
  - Identify the object
  - Segment object parts
- Classification
  - Classify each object part
  - Label the parts

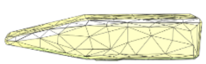




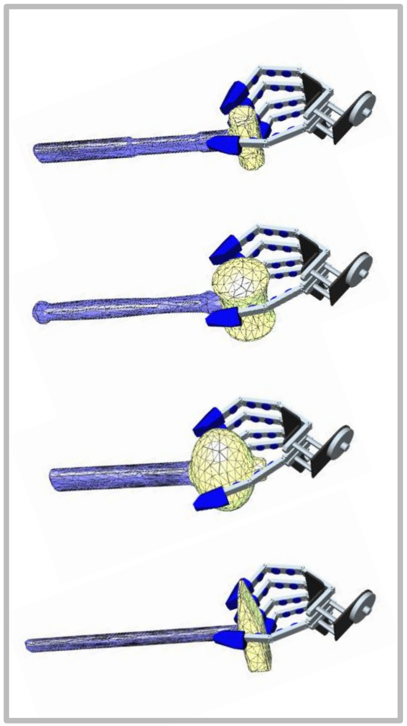
Online: Grasp Transfer to Novel Object

Task Constraints

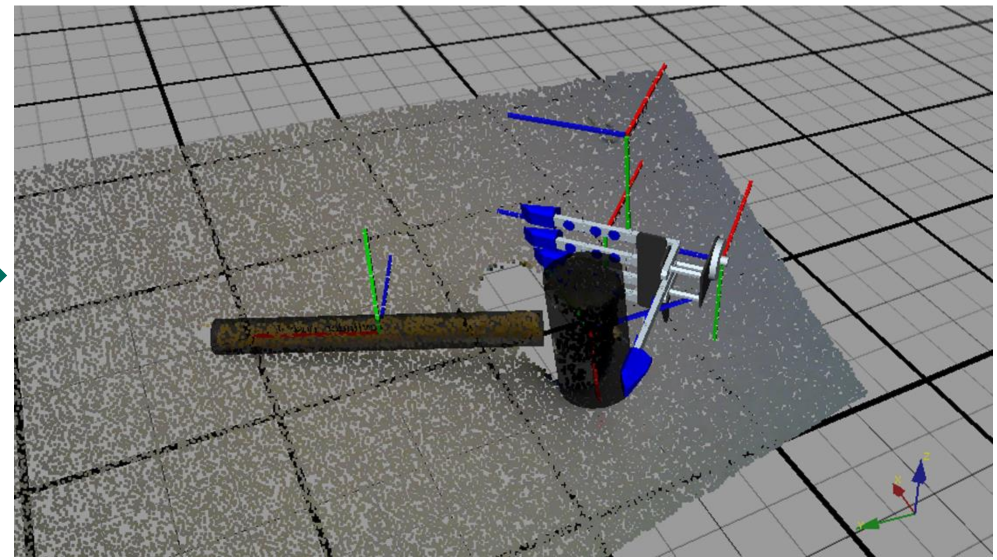
Object Part Selection



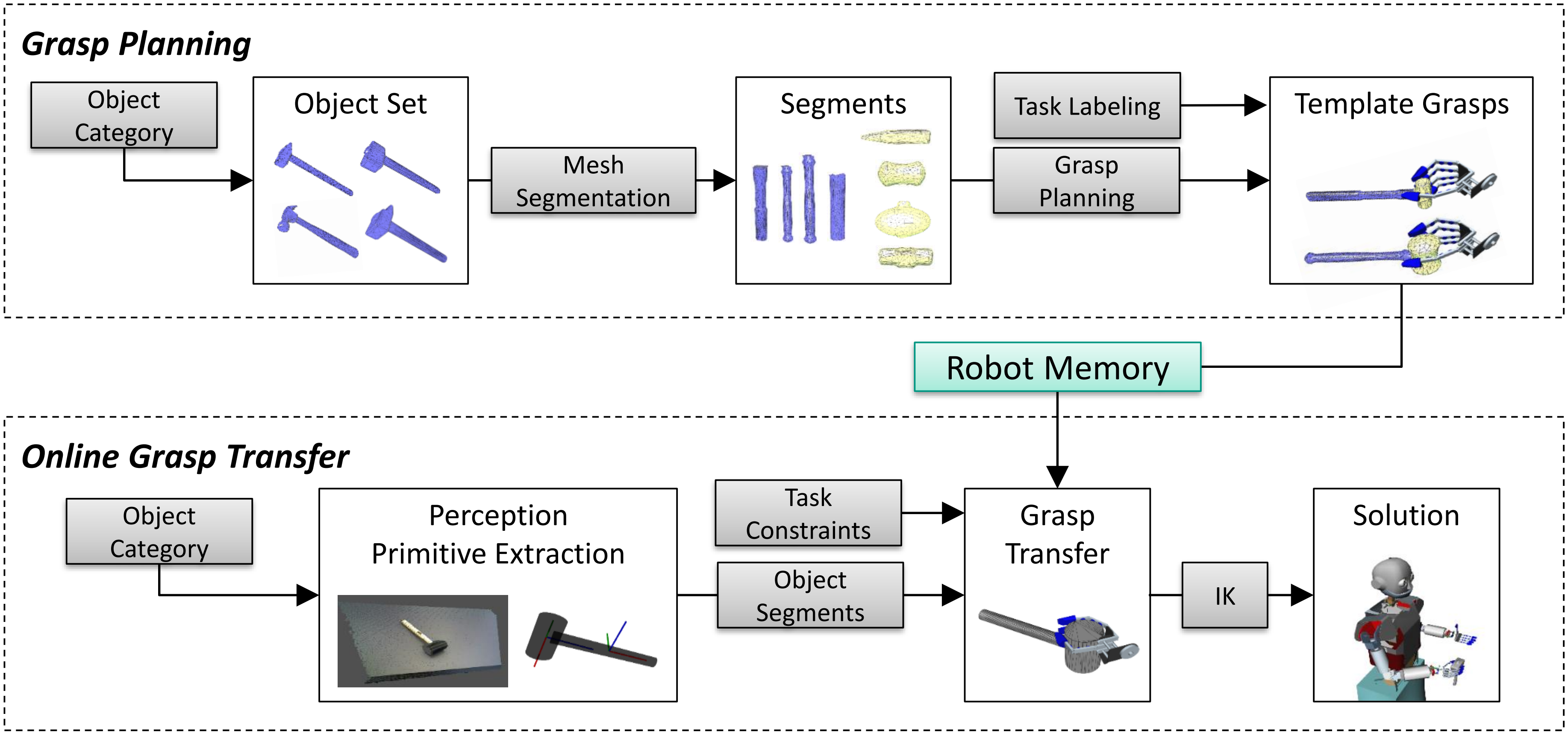
Template Grasps



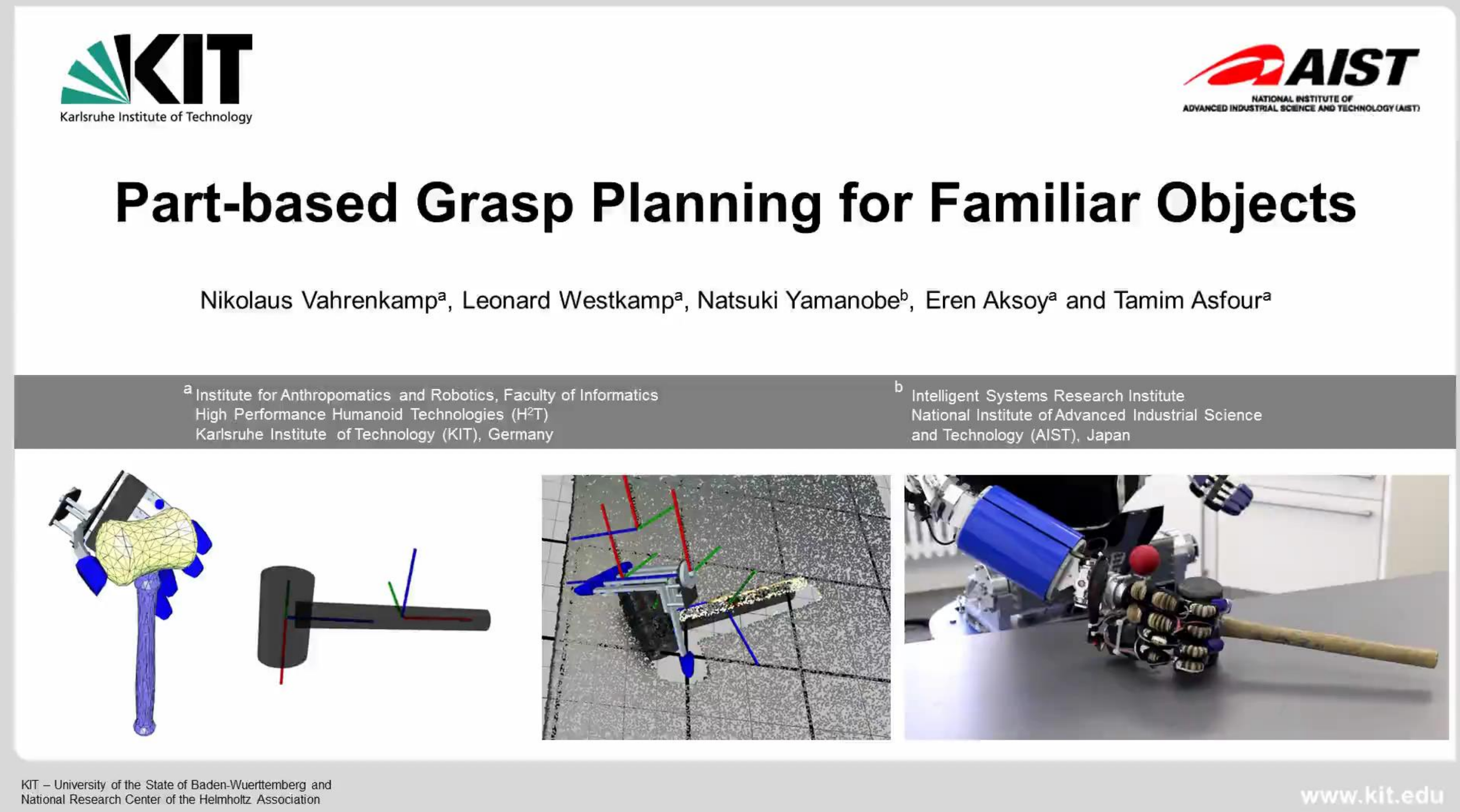
Grasp Transfer



Part-Based Grasp Planning: Architecture



Part-based Grasp Planning: Video



Grasping Unknown Objects: Concept

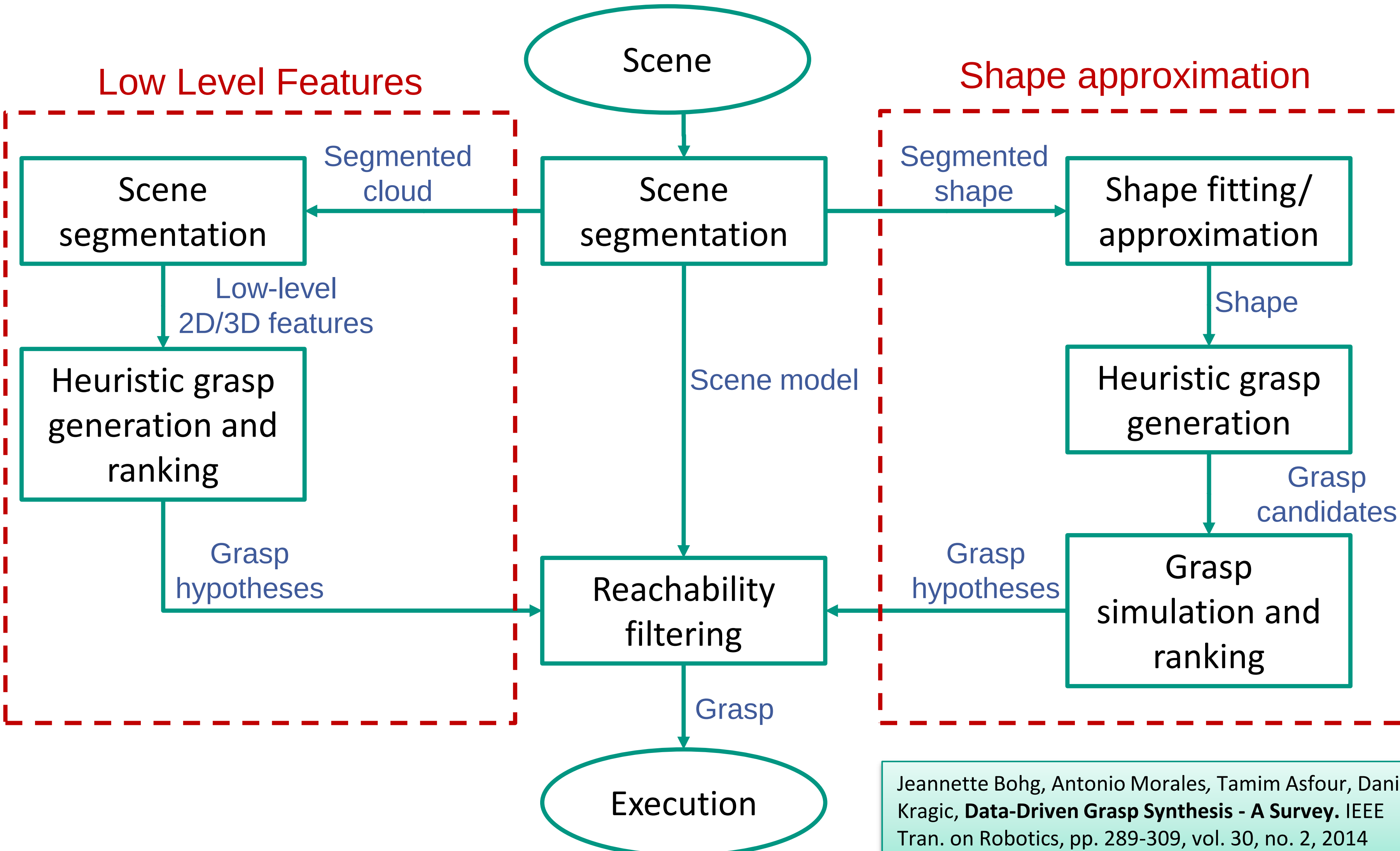
- How to grasp unknown objects?
  - Object model is not available
  - No access to similar objects or grasp experiences

- Mapping: Noisy sensor data → Candidate grasps

- Approaches can be divided into two methods
  - Approximating unknown object shape
  - From low-level features to grasp hypotheses

Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

Grasping Unknown Objects: Flow-Chart



Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

Approximating Unknown Object Shape

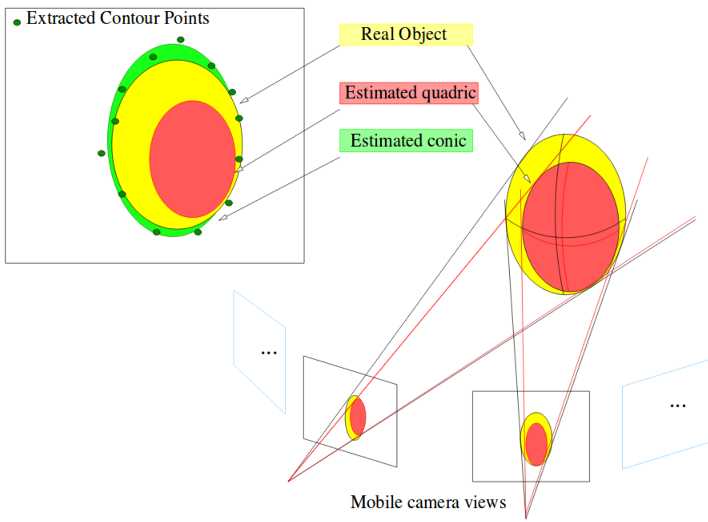
- Idea
  - Approximate object shape using shape primitives
  - Plan grasp on approximated shape

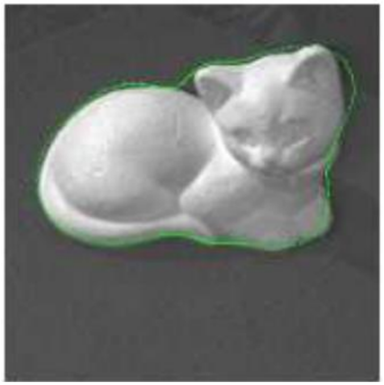
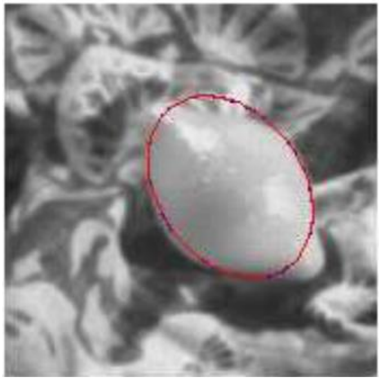
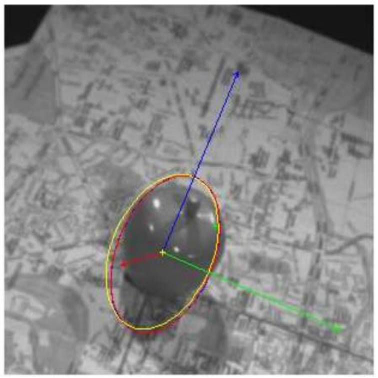
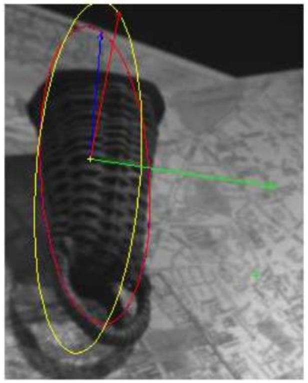
- Input options
  - Monocular images
  - Stereo images
  - RGBD data (point cloud)

- Shape approximation methods
  - Quadrics
  - Local normal estimation
  - Mesh construction (using symmetry)

Approximation using Quadrics: Dunes et al.

- Find a quadric that approximates the shape of the object
- Use of active vision (next chapter):
  - Gather multiple views of the object
  - Minimize uncertainty of parameters
  - Determine the next best view



C. Dunes, E. Marchand, C. Collowet, and C. Leroux, **Active Rough Shape Estimation of Unknown Objects**, in IEEE Int. Conf. on Intelligent Robots and Systems (IROS), 2008, pp. 3622–3627.

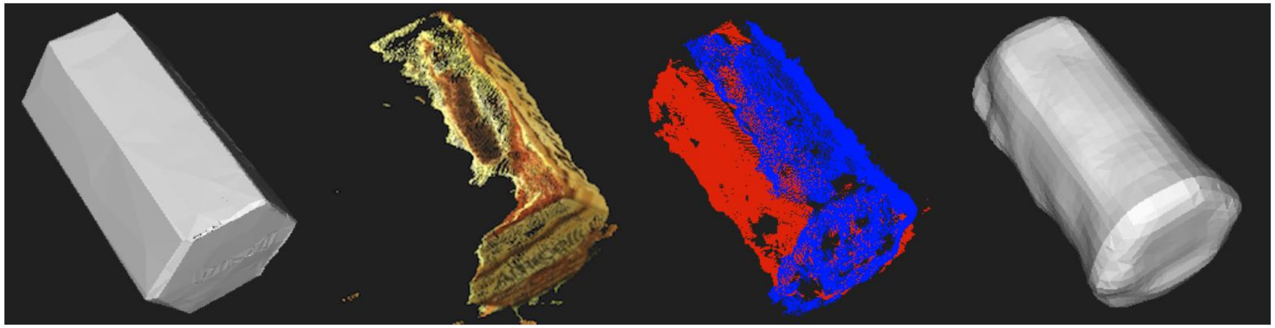
Approximation on point clouds: Marton et al.

- Input: Point cloud
- Initial step:
  - Estimation of **surface normal** and **minimal curve radius** for each point
- Different Surface estimation methods are tested:
  1. Fit boxes and cylinders
  2. Detect revolution surfaces
  3. Triangulate free form surfaces
- Grasp planning on estimated object surface

Z. C. Marton, D. Pangercic, N. Blodow, J. Kleinehellefort, and M. Beetz, **General 3D Modelling of Novel Objects from a Single View**, in IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2010, pp. 3700 – 3705.

Detecting and Using Symmetry: Bohg et al.

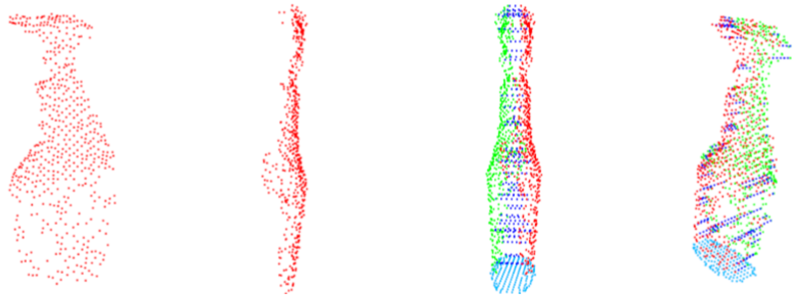
- Detect planar reflection symmetry in point cloud
  - Each point P can be uniquely associated with a second point Q by reflection on the opposite side of a **symmetry plane**
  - Iteratively improve and test hypothesis for symmetry plane
- Object shape completion
  - Create a mesh based on original and mirrored points
  - Use **Poisson reconstruction** to create a mesh
- Plan grasps on the completed object shape



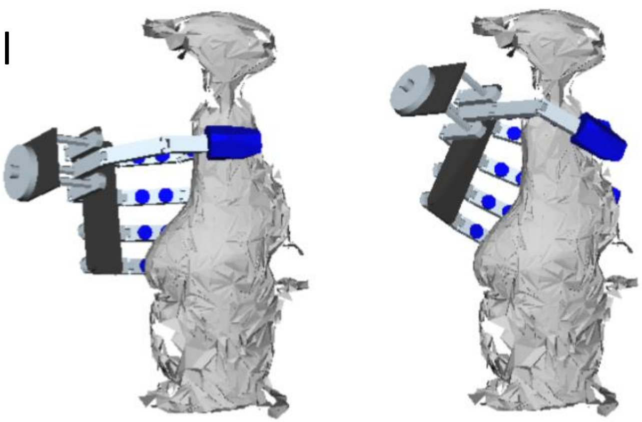
J. Bohg, M. Johnson-Roberson, B. León, J. Felip, X. Gratal, N. Bergström, D. Kragic, and A. Morales, **Mind the Gap – Robotic Grasping under Incomplete Observation**, in IEEE Int. Conf. on Robotics and Automation (ICRA), 2011.

Shape completion: Schiebener et al.

- Use planar reflection symmetry
  - Still holes in the point cloud
  - Additional completion steps



- Sides of the object
  - Projection into the camera plane
  - Subdivide image into horizontal segments
  - Find minimal and maximal point in horizontal direction
  - Connect with mirrored points



- Bottom of the object
  - Use supporting plane

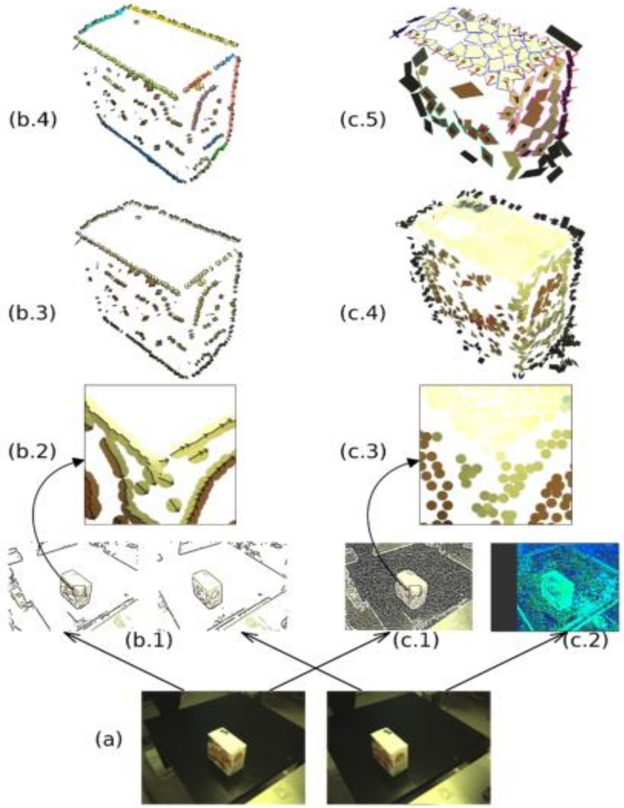
Schiebener, David, et al. **Heuristic 3D object shape completion based on symmetry and scene context**. Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on. IEEE, 2016.

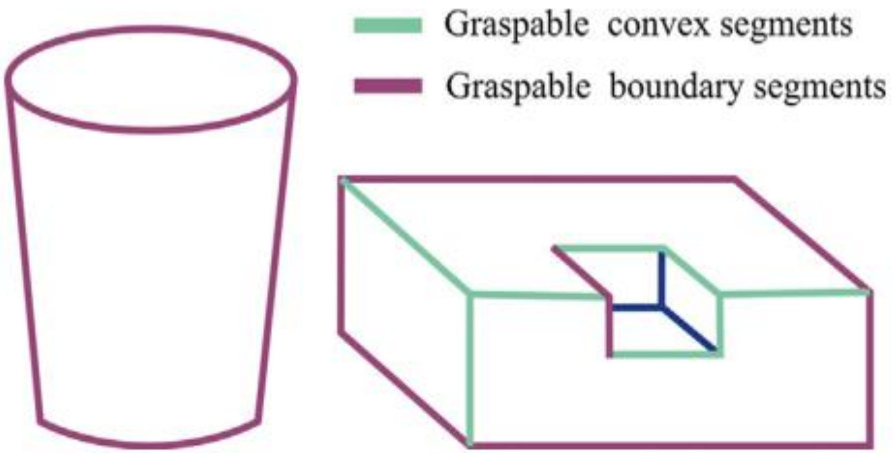
From Low-Level Features to Grasp Hypotheses

- Step1: Vision/Image Processing
  - Edge detection
  - Surface detection
- Step 2: Abstract elements extraction
  - Edge based
  - Surface based
- Step 3: Geometry analysis for grasping
  - Edge based
  - Surface based

From Low-Level Features to Grasp Hypotheses

- Early Cognitive Vision (ECV) based Elementary Grasping Action (EGA) (Kraft et al 2009, Popovic et al. 2011)
- Graspable Boundary and Convex Segments (RajeshKanna et al 2015)





ECV based EGA (Kraft et al 2009, Popovic et al. 2011)

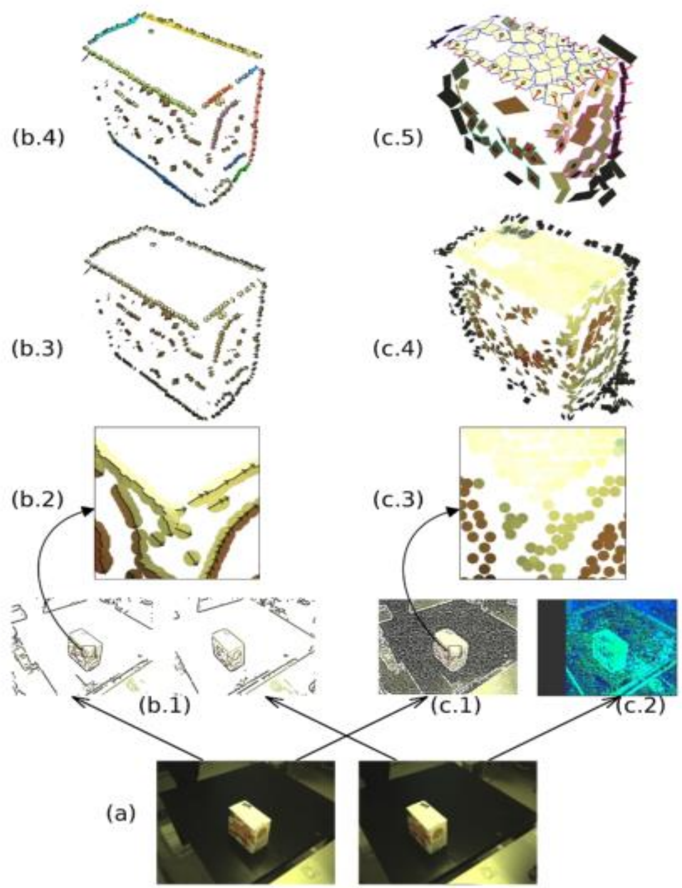
- Hierarchical ECV system (Step1: Vision/Image Processing)

3D contours

3D line segments

2D line segments

- Proximity
- Collinearity
- Co-circularity
- Similar appearance



3D surflings

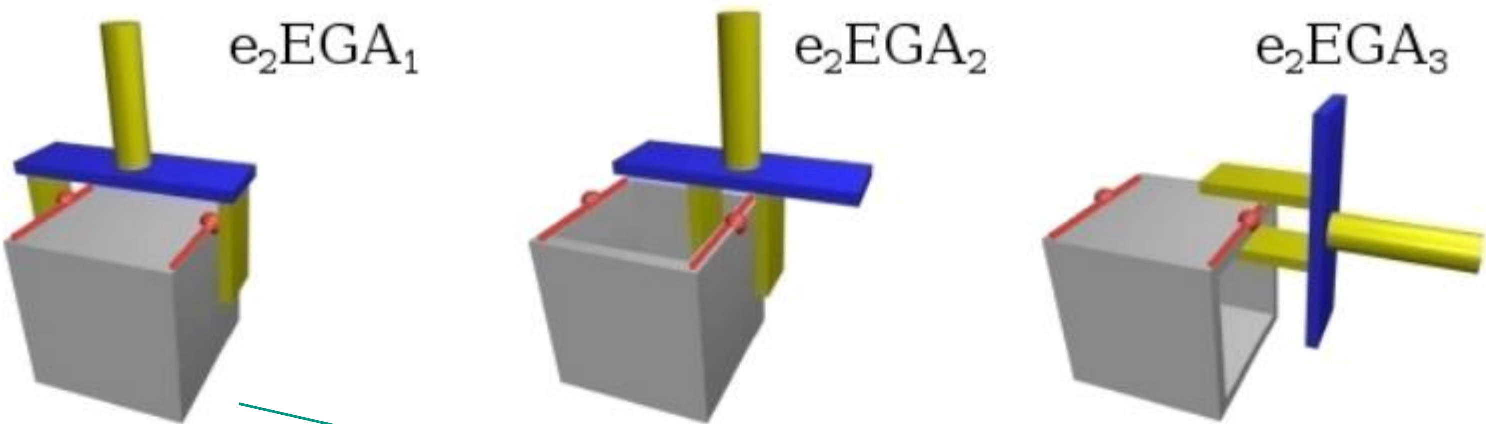
3D texlets

2D texlets

- Color
- Position
- Orientation

ECV based EGA (Kraft et al 2009, Popovic et al. 2011)

- Edge Elementary Grasping Action
  - Extract abstract contours (Step 2: Abtract elements extraction)
  - Generate edge based grasping actions (Step 3: Geometry analysis for grasping)

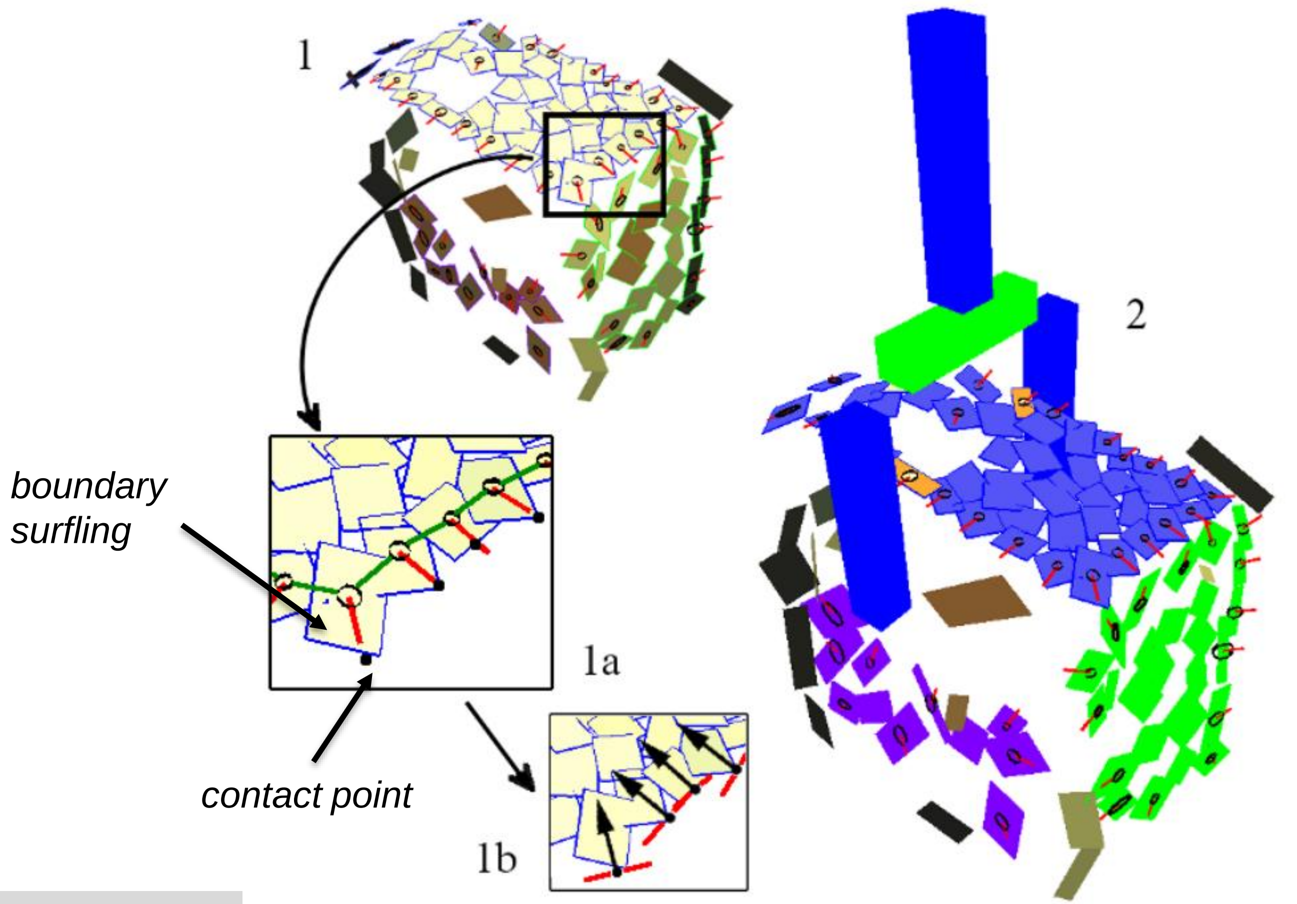


Geometry Analysis

Find a pair of contours with similar properties (co-planarity and co-colority)

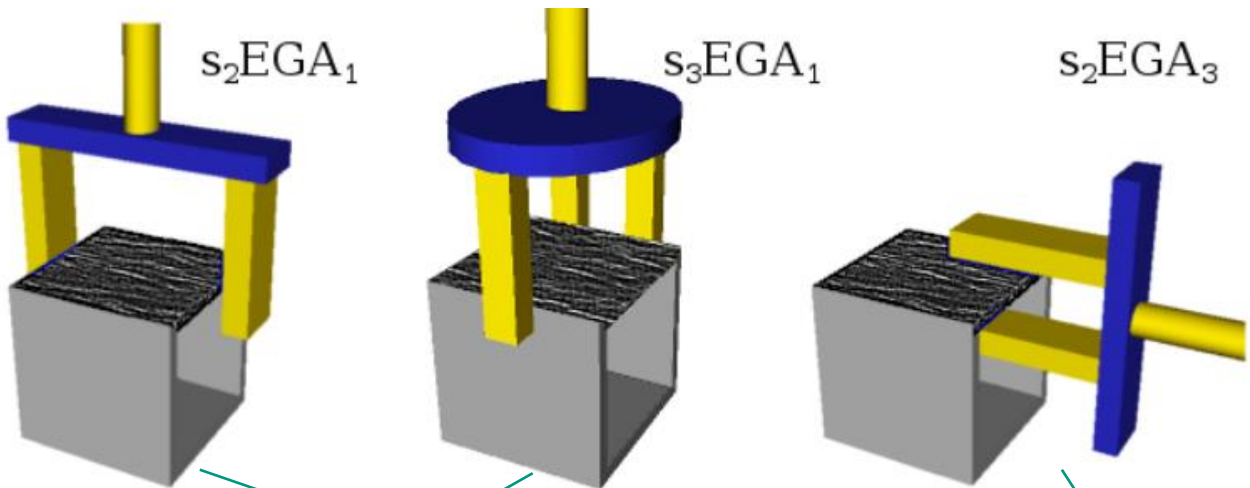
ECV based EGA (Kraft et al 2009, Popovic et al. 2011)

- Surface Elementary Grasping Actions
  - Contact points extraction (Step 2: Abtract elements extraction)



ECV based EGA (Kraft et al 2009, Popovic et al. 2011)

- Surface Elementary Grasping Actions
  - Contact points extraction (Step 2: Abtract elements extraction)
  - Contact points selection (Step 3: Geometry analysis for grasping)



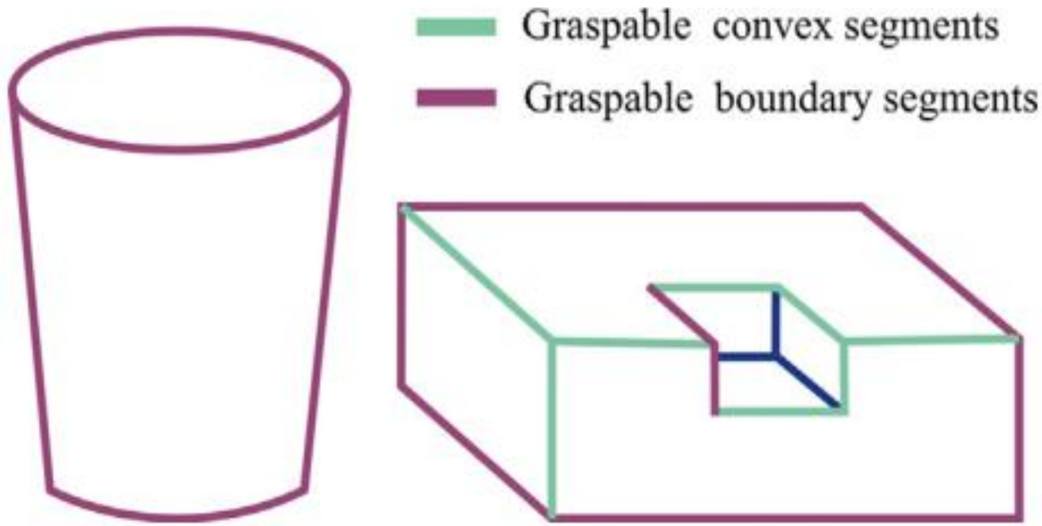
Geometry Analysis

Constraints (in the order):
1. Contact combinations are too far apart;
2. The angle between contact normal and direction of the force (stable grasping);

Pinch grasps: any contact points generate a valid grasping attempt

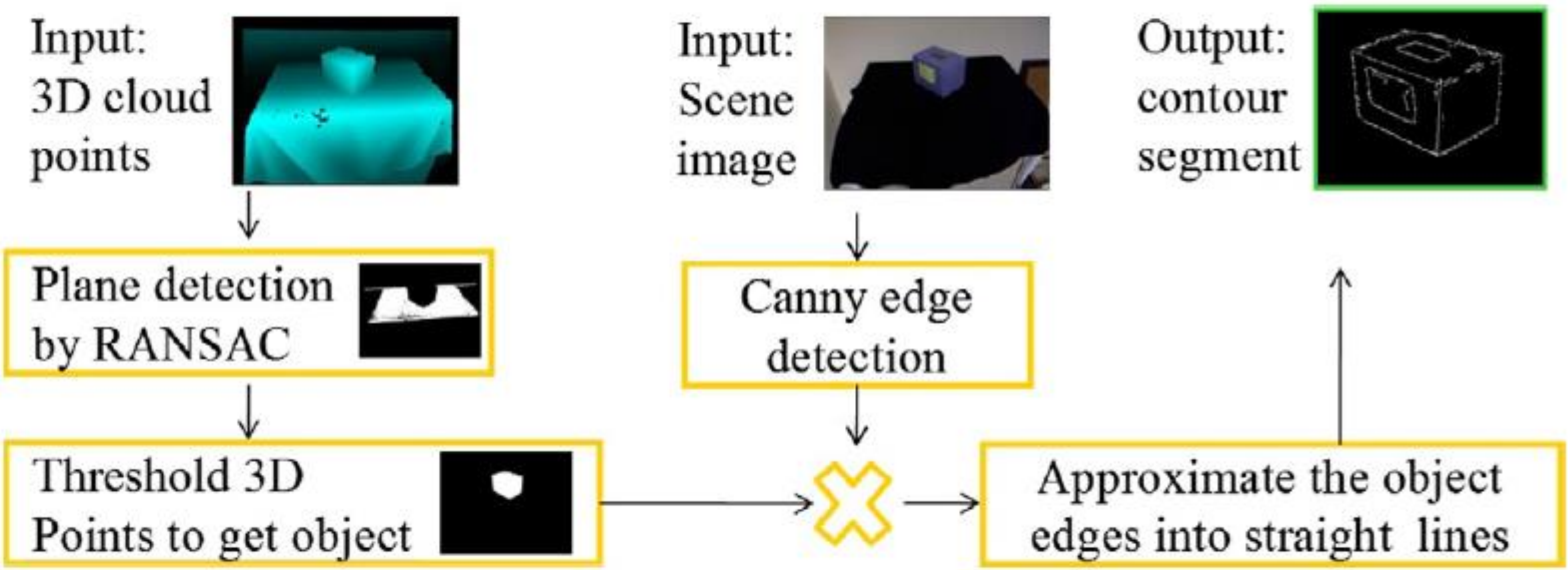
Graspable boundary and convex segments (RajeshKanna et al 2015)

- Grasplet
  - Graspable boundary segment: A segment that corresponds to a 3D spatial discontinuity.
  - Graspable convex segment: A segment along which the angle between the two faces forming the segment is greater than 180 deg.



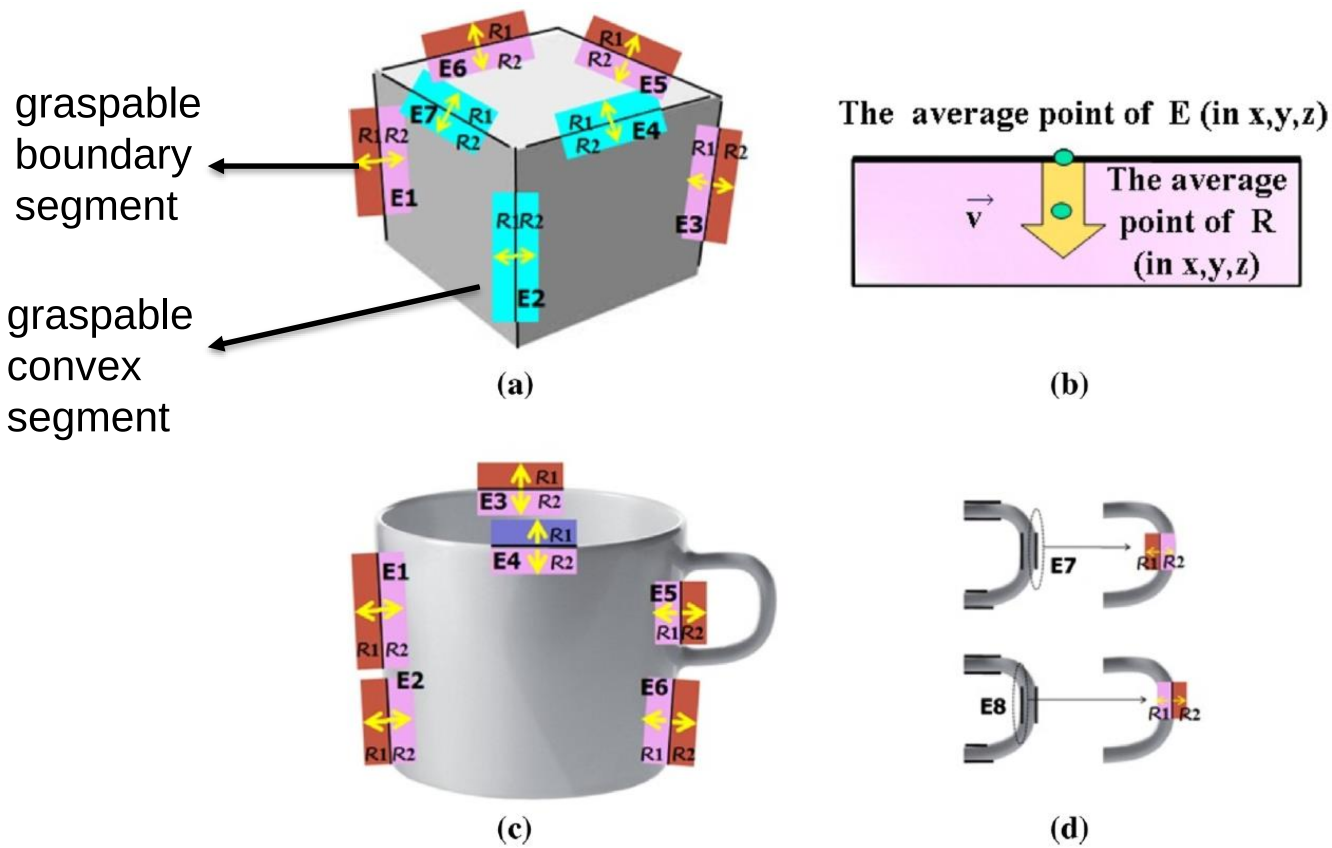
Graspable boundary and convex segments (RajeshKanna et al 2015)

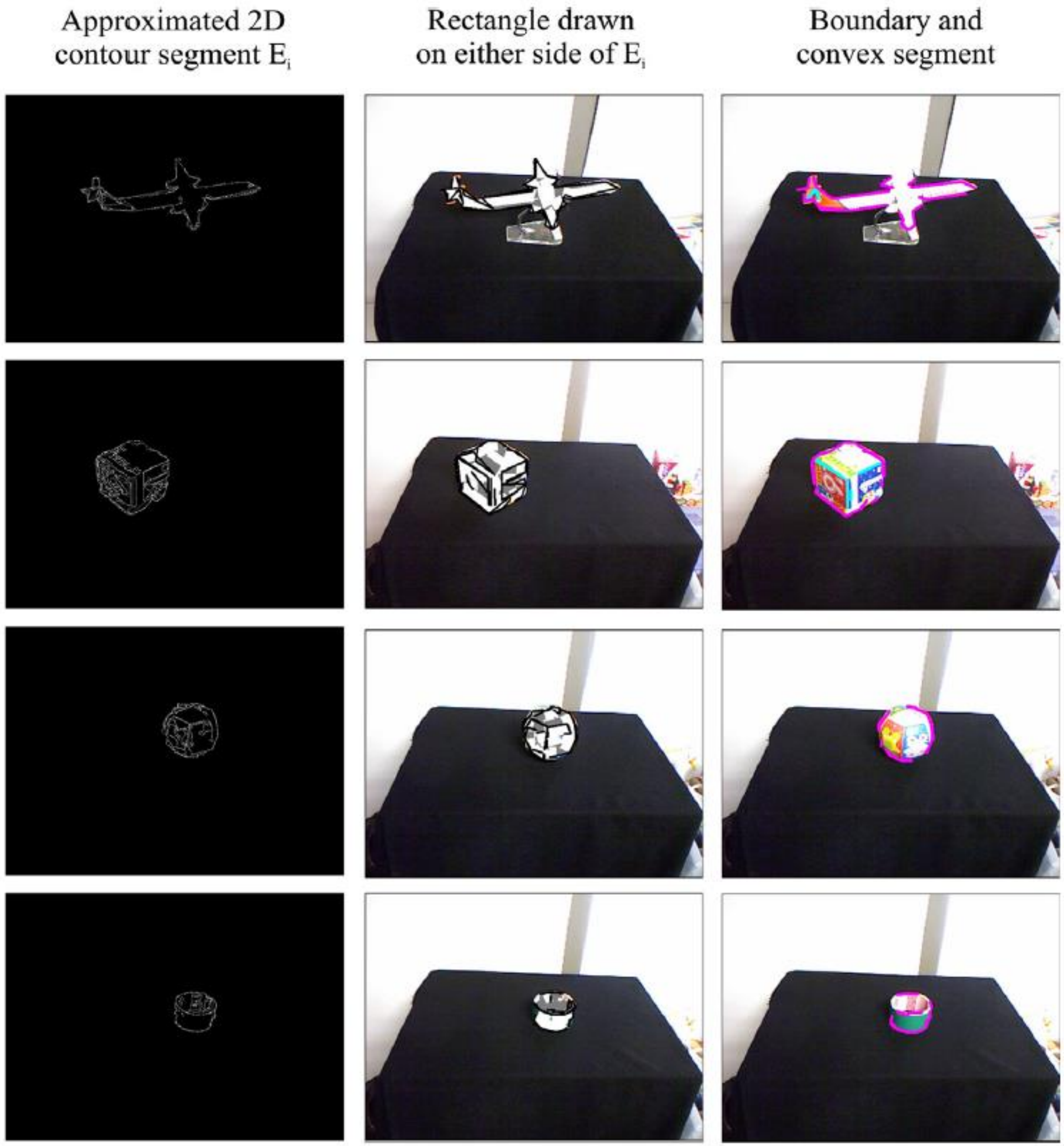
- Contour segments (Step1: Vision/Image Processing)



Graspable boundary and convex segments (RajeshKanna et al 2015)

- Grasplets extraction (Step2: Abtract elements extraction)



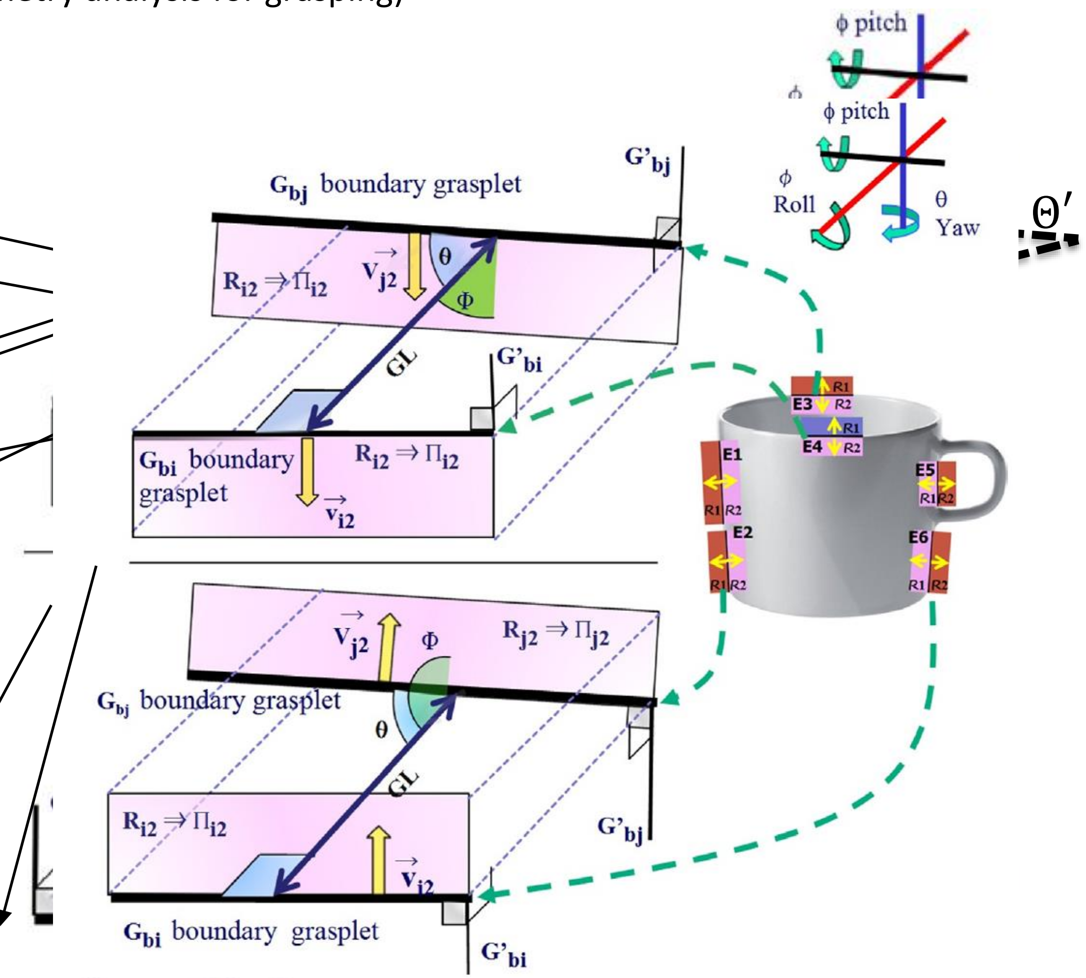

Approximated 2D contour segment E_i
Rectangle drawn on either side of E_i
Boundary and convex segment

Graspable boundary and convex segments (RajeshKanna et al 2015)

- Grasping generation (Step 3: Geometry analysis for grasping)

Steps:

1. Draw line
   - $GL\ s.t.\ GL \perp G_{ni}, GL \perp G_{nj}$
   - $G'_{ni}\ s.t.\ G'_{ni} \perp GL, G'_{ni} \perp G_{ni}$
   - $G'_{nj}\ s.t.\ G'_{nj} \perp GL, G'_{nj} \perp G_{nj}$
2. Calculate angles
   - $\theta' := \angle G_{nj}, GL$
   - $\Theta' := \angle G'_{ni}, G'_{nj}$
   - $\phi' := \angle \Pi_{im}, \Pi_{jm}$
3. Grasping decision
   $\theta' \approx 90^o, \Theta' \approx 0^o, \phi' \approx 180^o$
   - $\vec{V}_{im}$ and $\vec{V}_{jm}$ are inward and in opposite direction => PLANAR grasp
   - $\vec{V}_{im}$ and $\vec{V}_{jm}$ are parallel and in same direction => PARALLEL grasp



Graspable bc